

Mesomeris, S. (2004). Three essays on stock returns predictability and trading strategies to exploit it. (Unpublished Doctoral thesis, City University London)



**CITY UNIVERSITY
LONDON**

[City Research Online](#)

Original citation: Mesomeris, S. (2004). Three essays on stock returns predictability and trading strategies to exploit it. (Unpublished Doctoral thesis, City University London)

Permanent City Research Online URL: <http://openaccess.city.ac.uk/8436/>

Copyright & reuse

City University London has developed City Research Online so that its users may access the research outputs of City University London's staff. Copyright © and Moral Rights for this paper are retained by the individual author(s) and/ or other copyright holders. All material in City Research Online is checked for eligibility for copyright before being made available in the live archive. URLs from City Research Online may be freely distributed and linked to from other web pages.

Versions of research

The version in City Research Online may differ from the final published version. Users are advised to check the Permanent City Research Online URL above for the status of the paper.

Enquiries

If you have any enquiries about any aspect of City Research Online, or if you wish to make contact with the author(s) of this paper, please email the team at publications@city.ac.uk.

Three Essays on Stock Returns Predictability and Trading Strategies to Exploit It

by

Spyros Mesomeris

**A thesis submitted for the degree of Doctor
of Philosophy (Ph.D.) in Finance**

**City University
Cass Business School
Faculty of Finance**

August 2004

CONTENTS

	Abbreviations	iv
	List of Tables	vi
	List of Figures	vii
	Acknowledgements	viii
	Declaration	ix
	Abstract	x
Chapter 1	Introduction, Motivation, and Significance of the Study	
	1.1 Introduction	1
	1.2 Background of the study	2
	1.2.1 The Efficient Market Hypothesis	2
	1.2.2 The Martingale and Random Walk Models	5
	1.3 Mean Reversion in Equity Prices	6
	1.4 Long Memory in Equity Prices	9
	1.5 Exploiting Persistence with Technical Trading Rules	10
	1.6 Statistical Arbitrage	10
	1.7 The Problem Statement	11
	1.7.1 Motivation for the First Research Project	12
	1.7.2 Motivation for the Second Research Project	15
	1.7.3 Motivation for the Third Research Project	18
	1.8 The Significance of the Thesis	21
	1.8.1 Contributions of Chapter 2	21
	1.8.2 Contributions of Chapter 3	22
	1.8.3 Contributions of Chapter 4	23
	1.9 Organization of the Thesis	24
Chapter 2	Mean Reversion in Equity Prices: The G-7 Evidence	
	2.1 Introduction	25
	2.2 Literature Review	28
	2.2.1 Correlation/Regression and Variance Ratio Tests	28
	2.2.2 Tests of Relative Mean Reversion	36
	2.2.3 Theoretical Justifications and Further Empirical Evidence	38

2.2.3.1 Fads or Irrational Bubbles	38
2.2.3.2 Time-Varying Risk Premium	38
2.2.3.3 The Bandwagon Effect	39
2.2.3.4 Strategic Trading	40
2.2.3.5 The Overreaction Hypothesis	42
2.3 The Continuous Time Stock Price Model	45
2.3.1 The Model	45
2.3.2 Investment Horizon and Autocorrelation Coefficients	49
2.4 Empirical Methodology	52
2.5 Data and Empirical Results	55
2.5.1 Description of the Data	55
2.5.2 Empirical Results	56
2.5.3 Dynamic Simulations	59
2.6 Conclusion	59

Chapter 3 On the Returns Generating Process and the Profitability of Trading Rules in Emerging Capital Markets

3.1 Introduction	64
3.2 Literature Review	67
3.2.1 Parametric Long Memory Models	67
3.2.2 Empirical Evidence of Long Memory	74
3.2.3 Studies of Technical Trading Rules in Stock Markets	78
3.3 The Econometric Framework	82
3.3.1 Motivation	82
3.3.2 The ARFIMA-FIGARCH Model	83
3.3.3 Brakes in the Structural Breaks	85
3.4 Technical Trading Rules and the Bootstrap	87
3.4.1 Previous Evidence in ECM	87
3.4.2 Trading Strategy Methodology	88
3.4.3 The Bootstrap Methodology	92
3.5 Data	95
3.6 Empirical Results	97
3.6.1 Summary Statistics	97
3.6.2 Econometric Results	98
3.6.3 Trading Rule and Bootstrap Test Results	99
3.6.4 Effects of the Asian Crisis	106
3.6.5 “Double-or-Out” Strategy Results	108
3.7 Conclusion	111

Chapter 4	Testing Dividend Announcement Strategies in the UK for Statistical Arbitrage	
4.1	Introduction	125
4.2	The Limits of Arbitrage	128
4.3	The Notion of Statistical Arbitrage	132
4.4	Empirical Evidence on “Relative Value” Statistical Arbitrage	134
4.5	Statistical Arbitrage, Securities Prices, and Market Efficiency	137
4.6	Statistical Arbitrage and Market Anomalies	143
4.7	Signaling Theory and Implications for Dividend Announcements	147
	4.7.1 Empirical Evidence	147
	4.7.2 Post-Announcement Long-Term Abnormal Returns	149
4.8	Empirical Methodology	156
	4.8.1 The Statistical Arbitrage Test	156
	4.8.2 Correlated Incremental Trading Profits	159
	4.8.3 Probability of Loss	160
4.9	Data	161
4.10	Dividend Announcement Trading Strategies	163
	4.10.1 Transaction Costs	164
4.11	Empirical Results	165
4.12	Conclusion	173
Chapter 5	Summary, Discussion, and Further Research	
5.1	Introduction	178
5.2	Summary and Discussion of Results	179
	5.2.1 Chapter 2	179
	5.2.2 Chapter 3	181
	5.2.3 Chapter 4	184
5.3	Delimitations and Further Research	187
	References	190
	Appendices	
	Appendix 2.1	214
	Appendix 2.2	218

Abbreviations

ABM	Arithmetic Brownian Motion
ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller Unit Root Test
AIC	Akaike Information Criterion
AMEX	American Stock Exchange
APT	Arbitrage Pricing Theory
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BDS	Brock, Dechert, and Scheinkman Independence Test
CAPM	Capital Asset Pricing Model
CM	Constrained Mean Model
DF	Dickey-Fuller Unit Root Test
DJIA	Dow Jones Industrial Average
ECM	Emerging Capital Markets
EGARCH	Exponential Generalized Autoregressive Heteroskedasticity
EMH	Efficient Market Hypothesis
FIGARCH	Fractionally Integrated Generalized Autoregressive Heteroskedasticity
FTSE	Financial Times Stock Exchange
GARCH	Generalized Autoregressive Heteroskedasticity
GMM	Generalized Method of Moments
G-7	The 7 biggest industrialized economies

IFS	International Financial Statistics
IGARCH	Integrated Generalized Autoregressive Heteroskedasticity
IID	Identically Independently Distributed
IMF	International Monetary Fund
INI	(Dividend) Initiation
LSPD	London Share Price Database
MA	Moving Average
MSCI	Morgan Stanley Capital International
MLE	Maximum Likelihood Estimation
MSE	Mean Squared Error
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OECD	Organization for Economic Co-Operation and Development
OLS	Ordinary Least Squares
OMI	(Dividend) Omission
PAO	Pure Arbitrage Opportunity
QMLE	Quasi Maximum Likelihood Estimation
RMSE	Root Mean Squared Error
SA	Statistical Arbitrage
SAO	Statistical Arbitrage Opportunity
SBC	Scwarz Bayesian Criterion
SEDOL	Stock Exchange Daily Official List
SETS	Stock Exchange Electronic Trading System
S&P	Standard and Poors
TRB	Trading Range Break
UM	Unconstrained Mean Model
VMA	Variable Moving Average

List of Tables

Table 2.1:	Formulae for the Recovery of the Continuous Time Parameters	61
Table 2.2:	Summary Statistics	61
Table 2.3:	Continuous Time Parameters (Dividend Exclusive)	62
Table 2.4:	Continuous Time Parameters (Dividend Inclusive)	62
Table 2.5:	Dynamic Simulations	63
Table 3.1:	Summary Statistics for Asian Market Returns	113
Table 3.2:	Summary Statistics for Latin American Market Returns	114
Table 3.3:	Econometric Models for Asian and Latin AmericanMarket Daily returns	115
Table 3.4:	Results for Technical Trading Rules in Asian Markets	116
Table 3.5:	Results for Technical Trading Rules in Latin American Markets	117
Table 3.6:	Simulation Tests from Model Bootstraps for Individual VMA Rules	118
Table 3.7	Simulation Tests from Model Bootstraps for Individual TRB Rules	119
Table 3.8:	Simulation Tests from Model Bootstraps, VMA Rule Averages	120
Table 3.9:	Simulation Tests from Model Bootstraps, TRB Rule Averages	121
Table 3.10:	Results for VMA Rules in Asian Markets Excluding the Asian Crisis Period	122
Table 3.11:	“Double-or-Out” VMA Rule Strategy Returns and Break-Even Costs	123
Table 3.12:	“Double-or-Out” TRB Rule Strategy Returns and Break-Even Costs	124
Table 4.1:	Summary Statistics for the Incremental Profits from Dividend Announcement Strategies	175
Table 4.2:	Constrained Mean Correlated (CMC) Statistical Arbitrage Tests	176
Table 4.3:	Comparison Between Constrained Mean Correlated (CMC) and Unconstrained Constrained Mean Correlated (CMC) Models	177

List of Figures

Figure 2.1:	The effect of the Mean Reverting Parameter on the Autocorrelation Coefficient Across Investment Horizons	51
Figure 4.1:	Comparison of the Discounted Cumulative Profits of the Equal-Weighted Dividend Initiation Strategies	167
Figure 4.2:	Comparison of the Discounted Cumulative Profits of the Value-Weighted Dividend Initiation Strategies	168
Figure 4.3:	Probability of a Loss and Time-Averaged Variance for the Equal-Weighted Initiation Strategies that Represent Constrained Mean (CM) Statistical Arbitrage Opportunities	169
Figure 4.4:	Probability of a Loss and Time-Averaged Variance for the Value-Weighted Initiation Strategies that Represent Constrained Mean (CM) Statistical Arbitrage Opportunities	170

List of Figures

Figure 2.1:	The effect of the Mean Reverting Parameter on the Autocorrelation Coefficient Across Investment Horizons	51
Figure 4.1:	Comparison of the Discounted Cumulative Profits of the Equal-Weighted Dividend Initiation Strategies	167
Figure 4.2:	Comparison of the Discounted Cumulative Profits of the Value-Weighted Dividend Initiation Strategies	168
Figure 4.3:	Probability of a Loss and Time-Averaged Variance for the Equal-Weighted Initiation Strategies that Represent Constrained Mean (CM) Statistical Arbitrage Opportunities	169
Figure 4.4:	Probability of a Loss and Time-Averaged Variance for the Value-Weighted Initiation Strategies that Represent Constrained Mean (CM) Statistical Arbitrage Opportunities	170

Acknowledgments

I would like to take this opportunity to express my sincere gratitude to my supervisor, Dr John Hatgioannides, for his invaluable guidance and helpful suggestions throughout the Ph.D. process. I am grateful to Cass Business School for sponsoring me throughout the duration of my studies and to the people that helped to make this possible. Special thanks to my fiancé Maria for her continuous encouragement and patience, as well as computing assistance.

I would also like to thank Richard Baillie, Roy Batchelor, Blake LeBaron, Ana-Maria Fuertes, Marika Karanassou, and Mitchell Warachka for helpful discussions and comments. I also thank seminar participants at Cass Business School, London, and participants at the 2001 European Financial Management Conference in Lugano, Switzerland, the 2002 Multinational Financial Management Conference in Paphos, Cyprus, the 2003 WSEAS Conference in Athens, Greece, and the 2004 Australasian Finance Society Conference in Sydney, Australia.

Special thanks are due to my parents and my sister Kalia. Without their support and encouragement this dissertation would not have come into existence. Last, but not least, many thanks to the Ph.D. Director Proff. Giovanni Urga and the Ph.D. secretary Margaret Busgith for her patience and help.

Declaration

I grant powers of discretion to the University Librarian to allow this dissertation to be copied in whole or in parts without further reference to me. This permission covers only single copies made for study purposes, subject to normal conditions of acknowledgment.

Abstract

This thesis is organized in three self-contained projects which model predictability in both advanced and emerging stock markets and attempt to exploit it via construction of appropriate trading strategies. The objectives of this research are: 1) to model mean reversion in developed stock markets and re-assess the mixed empirical findings to date; 2) to characterize the returns generating process in emerging capital markets and examine the predictive ability and profitability of technical trading rules; 3) to develop and evaluate whether trading strategies involving dividend announcements in the UK are profitable and can be classified as statistical arbitrages, with consequent implications for the market efficiency hypothesis.

We investigate the existence of mean reversion in the G-7 economies using a two-factor continuous time model for national stock index data. Whilst maintaining the same modeling philosophy of previous studies, we rather focus on the effects of the “intrinsic” continuous time mean reverting coefficient. Our method produces support for mean reversion, even at low frequencies, and relatively small samples.

We also aim to characterize the stock return dynamics in four Latin American and four Asian emerging capital market economies and assess the profitability of popular trading rules in these markets. We find that dollar denominated returns exhibit statistically significant long memory effects in volatility but not in the mean. “Trading” our findings via a number of moving average and trading range break rules, we “beat” the buy and hold benchmark strategy in all markets before transaction costs, and in Asian markets even after transaction costs. Bootstrap simulations further reinforce the choice of the modeling framework and the trading outcomes, particularly for Latin American markets.

Finally, we investigate whether trading strategies designed to exploit “abnormal” price behavior following dividend initiation/resumption and omission announcements of UK firms pass the statistical arbitrage test of Hogan et al. (2004). To mitigate concerns regarding “risky” arbitrage, we also calculate the probability of making a loss for each strategy. We find that strategies involving portfolios of dividend initiating/resuming firms are profitable and converge to riskless arbitrages over time, while this is not the case for strategies with dividend omitting firms, contrary to what is suggested by US studies.

In general, the robustness of our results casts doubt on the market efficiency hypothesis in both developed and emerging capital markets.

Chapter 1: Introduction, Motivation, and Significance of the Study

1.1 Introduction

Finance students learn in their first year that any attempts to study historical data in search of that elusive gold mine are futile. The market quickly abolishes such pretensions. However, the truth is that since the 1980s a large number of empirical studies have brought under question the upholding arguments of the Efficient Market Hypothesis. One strand of the literature poses empirical challenges to the EMH in the form of systematic profitability of market anomalies strategies, such as the momentum and value strategies of Jegadeesh and Titman (1993, 2001) and Shleifer and Vishny (1994) respectively. With the advent of computing power and good quality data the study of technical analysis has re-emerged in academic circles, with some influential studies providing evidence in favor of the forecasting ability and potential profitability of technical trading rules (see, inter alia, Brock et al. (1992), Bessembinder and Chan (1998), Sullivan et al. (1999)). Other studies focus on the identification and modeling of predictable variations in security returns (eg. Fama and French (1998), Poterba and Summers (1988), Balvers et al. (2000)), and the exploitation of such predictability via simple arbitrage long-short type strategies (eg. De Bondt and Thaler (1985, 1987), Lehmann (1990), Chan et al. (1996), Balvers et al. (2000)). Whether predictability reflects the irrationality of investors and stock price “overreaction”/“underreaction”, limited arbitrage, or simply variations in ex-ante risk premia, the message is clear: Historical data do provide some information valuable for predicting future prices.

The primary objectives of the thesis are to model predictability in international stock markets and investigate whether such predictability can be exploited profitably by designing appropriate trading strategies. This study is organized in three self-contained projects

dealing with: Time series modeling techniques, technical analysis tools, and market anomaly strategies involving dividend announcements. Our data sets include both stock index and individual stock price data for both developed and emerging stock markets since the early 1980s. The data span coincides with the explosive growth of the hedge fund industry, and the availability of reliable data series and powerful computers which have moved the frontiers for the statistically interested investor and manager. The study will provide useful information to international investors and portfolio managers regarding profitable opportunities in a number of markets that differ in age, size, development and sophistication. Implications can be derived about the kind of trading strategies that would be promising in different markets. Our results may provide a comparative basis against which prior empirical studies carried out primarily in the US market may be evaluated.

The remaining of this introductory chapter covers the background to the study, describes the problem statement and its motivation, assesses the significance and finally outlines the structure of the thesis.

1.2 Background of the study

1.2.1 The Efficient Market Hypothesis

The Efficient Market Hypothesis (henceforth EMH) has a long history in finance, and its proponents are some of the most prominent figures in financial economics. Fama (1970) takes the market efficiency hypothesis to be the simple statement that security prices fully reflect all available information. Sufficient conditions for capital market efficiency under the above definition are that:

1. There are no transaction costs in trading securities.
2. All available information is costlessly available to market participants.

3. All market participants agree on the implications of current information for the current price and distributions of future prices of each security.

However, a frictionless market in which all information is freely available and investors agree on its implications is not descriptive of markets in practice. Therefore, Fama (1991) employs a weaker and economically more sensible version of the efficiency hypothesis, which says that prices reflect information until the marginal costs of obtaining information and trading no longer exceed the marginal benefit.

The above definition of efficiency is valid because the three conditions, even though sufficient for market efficiency, are not necessary. As long as investors take account of all available information, even large transaction costs that inhibit the flow of transactions do not themselves imply that when transactions do take place, prices will not “fully reflect” available information. The market may be efficient if “sufficient numbers” of investors have ready access to available information. Therefore, transaction costs are not necessarily sources of market inefficiency, even though they are potential sources.

Instead, the main obstacle to making inferences about market efficiency is that the hypothesis per se is not testable (Fama, 1991). It must be tested jointly with some model of equilibrium, or asset-pricing model, which provides a benchmark to how a market should price securities. Thus, when anomalous evidence on the behavior of returns is found, one is not sure how much of it to attribute to market inefficiency or to inappropriate model of market equilibrium.

In Fama (1970), the concept of efficient markets was formalized for the first time. He expresses the non-predictable characteristic of market prices formally as

$$E(\tilde{p}_{j,t+1}/\Omega_t) = [1 + E(\tilde{r}_{j,t+1}/\Omega_t)]p_{j,t}^1 \quad (1.1)$$

¹The expression $E(A/B)$ indicates the expected value of A given B has occurred.

where $p_{j,t}$ is the price of security j at time t , $r_{j,t+1}$ is the one-period percentage return, $(p_{j,t+1} - p_{t,j})/p_{t,j}$, Ω_t is the set of information available to investors at time t , and the tildes indicate random variables. The value of the equilibrium expected return $E(\tilde{r}_{j,t+1}/\Omega_t)$ based on the information set Ω_t would be determined from the particular expected return theory at hand. Expression (1.1), however, implies that whatever expected return model is assumed to apply, the information in Ω_t is fully utilized in determining equilibrium expected returns. It is in this sense in which Ω_t is “fully reflected” in the formation of the price. The major empirical implication of expression (1.1) is that the feasibility of trading systems, based solely on information in Ω_t , to produce profits in excess of equilibrium expected returns is ruled out.

According to Fama (1970), the EMH has three different shapes based on how “large” the information set Ω_t is:

- *Weak Form*: Ω_t includes just historical price or return sequences. If returns are not predictable from past returns, then new information is incorporated in the security price sufficiently fast so as not to allow investors to make excess returns by devising profitable trading rules. Once we have reached this state, the weaker form of the EMH will be satisfied.
- *Semi-strong Form*: Ω_t includes publicly available information such as dividends and earnings announcements, sales forecasts, merger announcements, etc. Fama (1991) uses the name event studies to describe semi-strong form tests of the adjustment of prices to public announcements. If this form of the EMH holds, then investors would be unable to earn an excess profit by purchasing/selling securities on the basis of such announcements.
- *Strong Form*: Ω_t reflects nonpublic information. This form of the EMH is examined by analyzing whether any group of investors (eg. hedge funds) can earn excess returns.

Empirical research on the theory of efficient markets has been concerned with whether prices “fully reflect” particular subsets of available information. The categorization of tests into weak, semi-strong, and strong form serves the useful purpose of allowing researchers to pinpoint the level of information at which the hypothesis breaks down.

1.2.2 The Martingale and Random Walk Models

Assuming no risk premium, market efficiency requires that

$$E(r_{j,t+1}/\Omega_t) = 1 + i_t \quad (1.2)$$

where i_t is the riskless interest rate. Defining $r_{j,t+1}$ as $p_{j,t+1}/p_{j,t}$, (1.2) can be reformulated as

$$\frac{1}{1 + i_t} E(p_{j,t+1}/\Omega_t) = p_{j,t} \quad (1.3)$$

This is a statement that the discounted price sequence for security j , $\{p_{j,t}\}$, follows a martingale with respect to the information sequence Ω_t .

Suppose $\Omega_t = \{p_{j,t}, p_{j,t-1}, \dots, p_{j,t-n}\}$. Then:

$$E(p_{j,t+1}/p_{j,t} \dots p_{j,t-n}) = (1 + i_t)p_{j,t} \quad (1.4)$$

According to (1.4), stock price movements are unpredictable. A special case of equation (1.4) is the “random walk” model, which under its simplest version gives the following dynamics for the price process

$$p_{j,t+1} = p_{j,t} + u_{t+1}, \quad \text{where } u_{t+1} \sim IID(0, \sigma^2)^2 \quad (1)$$

²A trivial generalization is the random walk model with drift μ :

$$p_{j,t+1} = \mu + p_{j,t} + u_{t+1}$$

That is, the error term is independently and identically distributed with mean 0 and variance σ^2 . This implies in turn that returns are independently and identically distributed with the same mean and variance (for the random walk with drift model, the mean of the returns μ is determined by risk factors). The martingale model does not make either of the two assumptions. In particular, it allows for dependence involving the higher conditional moments of returns. The importance of the distinction between the martingale and the random walk models is evident. Security prices are known to go through protracted quiet periods and sometimes equally protracted turbulent periods, rendering it possible for successive conditional variances of stock prices to be positively correlated.

Though insufficiently realized at first, early empirical tests of market efficiency which focussed on return autocorrelations were in fact tests of the martingale hypothesis (LeRoy, 1989). Initially, weak form tests focussed on short horizon returns, typically sampled at daily and weekly intervals, which allowed for large sample sizes. The early literature as summarized in Fama (1970), does not interpret the autocorrelation in short horizon returns as important evidence against the joint hypothesis of market efficiency and constant expected returns. Positive autocorrelations close to zero were dismissed as being of no economic significance to make any economic sense and were deemed indistinguishable from a random walk. Therefore, this early work largely concludes that the market is efficient.³

1.3 Mean Reversion in Equity Prices

The mean reversion literature has started as a spin-off of the literature on efficient capital markets, but has grown by now to become in itself one of the most significant issues in the financial economics literature. Mean reversion in stock prices describes the tendency

³Fama (1970) uses the term “random walk” rather casually. The fact that he interpreted near-zero autocorrelations, even though significant, as favoring market efficiency, suggests that he in fact identified efficiency with the characterization of returns as a martingale.

of stock prices to return to some trending level, i.e. it implies that shocks to prices are temporary, so that returns are negatively correlated at certain horizons. Mean reversion has been put forward as one of the main arguments against the random walk version of the EMH, since it implies that stock returns can be predicted from their past values. However, given the vast implications of mean reversion for risk management, asset and option pricing, and market timing, many researchers have concentrated on identifying and quantifying mean reversion as a property of asset prices, rather than treating it simply as a means to assess the EMH. As a result, a number of different methodologies have been developed to uncover and “measure” the extent of mean reversion in different data, often producing conflicting empirical results. Note that while the thesis focuses on stock markets, it has been documented that asset markets in general are mean reverting, prominently the commodity and foreign exchange markets.

The mean reversion literature challenges Fama’s (1970) interpretation of autocorrelations in short horizon returns. The majority of this literature proposes that instead of modeling the stock price as a martingale, analysts should consider assuming that price comprises a random walk plus a fads variable component.⁴ In doing so, the researcher takes the view that prices take large, slowly decaying swings away from their fundamental values, which could be caused by “fads” or irrational bubbles. Shiller (1984) and Summers (1986) were the first to present such stock price models. Summers (1986) showed that if a fads component such as this accounted for a large fraction of the variance of returns, the fads behavior might be difficult to detect by looking at short horizon autocorrelations of returns as those early tests had done. The intuition behind Summer’s reasoning was that if stock prices took large jumps away from their “fundamental” values, and then only reverted back towards the fundamental price over a period of years, the autocorrelations of daily, weekly, or even monthly returns would capture only a small fraction of this mean

⁴Thus, evidence of significant mean reversion would constitute evidence against the random walk form of the EMH, but not necessarily against the martingale version if it can be shown that when one accounts for time-varying volatility (or higher moments), the market is efficient.

reversion.

Shiller's (1984) and Summer's (1986) modeling philosophy motivated the celebrated papers of Fama and French (1988) and Poterba and Summers (1988), which model stock prices as having a permanent nonstationary (drift) component and a temporary stationary mean-reverting component. Since then, other statistical techniques have been employed to detect and model mean reversion, including cointegration tests (see, for example, Kasa (1992) and Richards (1995)) and panel data methodologies (eg. Balvers et al. (2000)). Despite the numerous papers in the area and the different approaches considered, Summer's (1986) observation that short-horizon tests simply lack the power to detect a slow mean-reverting price component still remains the paradigm for many researchers in the area of finance. This necessitates testing for mean reversion over long horizons using low frequency data, which in turn requires long data series for the tests to have satisfactory statistical properties. The unavailability of reliable data over the long spans required by mean reversion tests has fuelled the debate regarding the small-sample bias problems of mean reversion tests (eg. Richardson (1993) and Richardson and Stock (1989)) and has brought under question the very existence of mean reversion in equity prices.

Moreover, there seems to be a "confusion" in the literature regarding the properties of stock prices over different investment horizons, with conflicting evidence for different data sets. Although most empirical studies suggest that over "short" investment horizons (of up to a year) stock returns exhibit positive serial correlation (or momentum), with mean reversion setting in in the long-run (between one and five years), there is also evidence of return reversals even at shorter frequencies: monthly (Jegadeesh (1990)), weekly (Lehmann (1990)), and even at the daily frequency (Admati and Pfleiderer (1989) and Bessembinder and Hartzel (1993) for individual stocks).⁵ There is clearly room in the literature for attempting to rescue the confusion brought about by the specification of

⁵Daily return reversals in Admati and Pfleiderer (1989) and Bessembinder and Hartzel (1993) are theoretically motivated and cannot be attributed purely to microstructure biases.

different investment horizons, as well as for employing methodologies which obviate the need to use low-frequency data series that statistically purge findings of mean reversion.

1.4 Long Memory in Equity Prices

As discussed in the previous subsection, several studies find evidence of long horizon predictability in asset returns, contrary to the random walk hypothesis. Lo (1991) argues that such evidence may be symptomatic of a long range dependent (long-memory) component in stock market prices, allowing asset returns to exhibit significant autocorrelation between distant observations. The presence of long memory contradicts the weak form of the EMH. If the series realizations are not independent over time, then past returns can help predict future returns, giving rise to consistent speculative profits that can be exploited via appropriate trading rules. Consequently, a number of semi-parametric and parametric methodologies have been developed to investigate long-memory in asset returns, including the modified rescaled range statistic (R/S), which robustifies the rescaled range statistic of Hurst (1951) against short-run dependence, the Geweke and Porter-Hudak (1983) spectral regression method, and the parametric autoregressive fractionally integrated processes for the mean (ARFIMA) and the variance (FIGARCH). Thankfully for the proponents of the EMH, the evidence in favor of long memory in stock returns is rather scarce. Instead, persistence in the second moment of the asset returns process has recently attracted considerable attention. The slow decay of autocorrelations in the conditional variance is by now established as a “stylized fact”, with long memory models capable of (at least partially) accounting for empirical features such as volatility clustering and leptokurtosis in the distribution of returns.

Empirical studies investigating the presence of long memory in equity returns have focussed almost entirely on developed stock markets. To the best of our knowledge, little work has been conducted regarding long memory in emerging capital markets (ECM),

possibly due to the lack of sufficiently long data series sampled at high frequencies to allow for an adequate number of observations for model estimation.

1.5 Exploiting Persistence with Technical Trading Rules

The presence of predictability in asset prices either in the form of positive correlation, negative correlation, or long memory, does not imply inefficiency if the application of a known trading strategy does not generate systematic economic gains to its users. Technical analysts have long relied on the premise of predicting market returns through identifying patterns in past stock market prices. Belief in past price patterns in security movements violates the random walk version of the EMH if it results in producing significant abnormal returns.

Early empirical research (eg. Fama and Blume (1966), Jensen and Benington (1970)) has dismissed technical analysis as useless. However, the seminal paper by Brock et al. (1992), which demonstrated that a relatively simple set of technical trading rules possesses significant forecast power for changes in the Dow Jones Industrial Average (DJIA) over a long sample period, renewed academic interest in technical analysis. Thereafter, studies have verified that trading schemes involving moving average and channel rules have some forecast power for future price changes in stock and currency markets. It has not been clear though whether exploiting apparent trends in historic price data yields returns superior to a buy-and-hold strategy after accounting for the influence of transaction costs.

1.6 Statistical Arbitrage

“Statistical arbitrage” (SA) trading strategies are not a novel development in financial markets. Instead, they have been practiced by investment banks, hedge funds, and investment houses since the early 1980s. The term came to being with the realization that arbitrage activities do not conform to the textbook model of arbitrage which requires no

capital and entails no risk. The recognition that practical arbitrage strategies are risky, may involve intermediate losses, and often rely upon favorable statistical properties of the mispricing or deviation from the fair price relationship has led to the more general class of arbitrage strategies known as “statistical arbitrages”.

The premise of SA is that it may be possible to exploit statistical regularities in relative asset prices without the prior of a theoretical fair-price relationship between the set of assets involved. As such, SA opportunities are likely to be more persistent and prevalent in financial markets than standard arbitrage opportunities, even though clearly entailing a higher degree of “risk”. Two recent academic papers - Bondarenko (2003), Hogan et al. (2004) -, employ the SA terminology to derive empirically testable hypotheses for the existence of SA opportunities in an attempt to re-evaluate the EMH without invoking the joint hypothesis of a market equilibrium model. In particular, the methodology of Hogan et al. (2004) calls for a re-evaluation of the EMH paradigm by extending the definition of standard arbitrage to its infinite horizon counterpart (the Hogan et al. definition of SA), thus appealing to long-horizon (market anomaly) strategies to test the EMH. It is interesting in its own right to explore empirically market anomalies for SA at an international level, so as to draw conclusions regarding the EMH from a variety of markets. Also, tests of lesser known anomalies to the investment community (such as the alleged market anomaly following dividend announcements) could be particularly promising in the context of SA.

1.7 The Problem Statement

This thesis investigates predictability in both developed and emerging stock markets with a view to exploiting any apparent persistence in stock market returns to “beat the market”. In order to present the results in a meaningful and manageable manner, three self-contained projects are included in the thesis, forming the Chapters 2 to 4. In this

section we will state the motivation and objectives for each of the three projects separately.

1.7.1 Motivation for the First Research Project (Chapter 2)

Our interest in modeling mean reversion in equity prices stems both from the importance of mean-reverting patterns in stock returns for asset managers, risk managers, and traders, as well as from the existing modeling deficiencies of the empirical literature.

First, asset assessment, and consequently risk management, can be substantially biased if non-random behavior in equity markets is not accounted for. The impact of stock return predictability on risk assessment arises because when assets exhibit patterns (of non-randomness), their variance will vary disproportionately with the time interval. This means that one cannot, for example, use the variance of monthly returns to estimate the variance of yearly returns, or yearly returns to estimate the variance of ten-year returns, since they are not linearly related. In a mean reverting equity market, if the variance of short-term returns is transformed into longer-term measures of variance, long-term risk will be overstated. The implication of equity markets having potentially lower risk is clear. The lower the risk of the equity market, the larger the allocation to (weight of) equity should be.⁶ Barberis (2000) employs monthly data on the value-weighted index of NYSE stocks and compares two investment strategies: “Buy-and-hold” versus dynamic rebalancing, when stock market returns have a predictable component. He concludes that a risk-averse investor will allocate a larger proportion to equities, the longer the horizon, even when parameter uncertainty about the predictor variable exists.

Perhaps of more interest to asset managers is the potential that evidence for mean reversion has for timing the market. If markets are mean reverting, then a downward shock

⁶Using 200 years of US data (1802-1997), Siegel (1998) shows that in the long-term stocks are less risky than either long-term bonds or Treasury bills. Standard deviations of stock returns decline more rapidly with the investment horizon than the standard deviations of bond and bill returns. The reduced relative risk of stocks at long horizons, even with the simple standard deviation measure, provides indirect evidence for predictable variation in stock returns.

to the market will only cause a transitory drop to stock prices, which will be offset by subsequent gains. If significant bull markets occur shortly after significant bear markets, then there exist substantial buying opportunities after market crashes or downturns. This is how, for example, market timers can take advantage of mean reversion patterns. Of course, it would be ideal for market timers to establish whether there is some predictable interval over which stock markets are expected to mean revert. Though there is no conclusive evidence regarding this question, most studies point to a mean reversion half-life of a few years (eg. Fama and French (1988), Balvers et al (2000)).

Lo and Wang (1995) have shown that the predictability of an asset's return will affect the prices of options on that asset, especially those of longer maturity options. Changes in predictability affect the value of the diffusion (volatility) coefficient, which in turn affects option prices. Option values under the trending Ornstein-Uhlenbeck specification are always greater than, or equal to, option values calculated by the standard Black-Scholes formula.

A number of important issues emerge from the empirical literature on mean reversion which demand further investigation. First, the evidence on mean reversion is rather inconclusive, as it largely hinges upon the specification of the "holding time period" in stocks. However, the required length of the investment horizon that would give rise to mean reversion is not explicitly linked to any theoretical asset pricing model. The fads model and the time-varying risk premium explanations have more explanatory power for low-frequency returns, whereas strategic trading models rationalize the existence of price reversals even in daily data. On the contrary, the overreaction/partial adjustment to new information hypothesis has been advocated as a possible justification for mean reversion both for short holding periods (Lehmann (1990), Jegadeesh (1990)), and longer return intervals (De Bondt and Thaler (1985, 1987), Chopra et al (1993)). If we have no prior basis for choosing a particular return interval (lag), we may be overstating mean reversion

by focussing on the most significant lag.

Second, an important requirement of the existing approaches in testing for mean reversion is that long-time series need to be employed. As Balvers et al. (2000) put it, “a serious obstacle to detecting mean reversion is the absence of reliable long-time series, especially because mean reversion, if it exists, is thought to be slow and can only be picked up over long horizons” (p.746). Returns autocorrelations and variance ratio tests have little power to distinguish the random walk representation of stock prices from alternatives that imply highly persistent, yet transitory, price components. Poterba and Summers (1988) comment that the only solution to the problem of low power is the collection of more data. An additional complication is the fact that when testing for mean reversion with low frequency data (“long” investment horizons), little independent information is left. For example, in the Fama and French (1988) data set there are only twelve non-overlapping observations at the five-year horizon! The unavailability of reliable long time series has forced researchers to employ overlapping data, at the expense of introducing spurious correlation and biases to the estimated coefficients. Richardson and Stock (1989) and Richardson (1993) argue that correcting for small sample bias problems could reverse the Poterba and Summers (1998) and Fama and French (1988) results which favor mean reversion.

More evidence in support of mean reversion in stock prices is recently provided by Balvers et al. (2000) in their panel data study. The panel data format has the advantage of utilizing the cross-sectional variation in equity indices to increase the power of the test, but makes the restrictive assumption that the speeds of reversion towards a common stochastic trend path in different countries are similar. Moreover, tests for relative mean reversion do not specify a fundamental or trend path for the series under investigation, and do not capture the intuitive notion of the stock price returning to its own trend path.

The main objective of Chapter 2 is to develop a methodology for modeling mean

reversion, which, while consistent with the previous literature and proposed theories to rationalize mean reversion, it does not rely on an “occasional” and perhaps arbitrary choice of the investment horizon. The second objective is to allow testing for mean reversion without the need to employ long time series, or overlapping data in the estimation procedures. Finally, to empirically evaluate mean reversion in stock index prices of the G-7 economies using recent data and compare results with existing studies. We have chosen to apply our methodology in the major developed markets which have witnessed a fast growth of index option markets in the last few years, since the methodology is particularly suited to pricing index options in a mean-reverting framework in the spirit of Lo and Wang (1995).

1.7.2 Motivation for the Second Research Project (Chapter 3)

Chapter 3 investigates returns and volatility dynamics in eight emerging capital markets (ECM) from Asia and Latin America based on the general double long-memory ARFIMA-FIGARCH model, and in addition assesses the profitability of popular trading rules in these markets.

In recent years ECM have attracted a great deal of attention from investors and portfolio managers. This is not only because the ongoing process of liberalization has opened up new, previously unexplored markets to the international investment community, but more importantly because some characteristics of these stock markets render them particularly attractive. Portfolio managers can exploit the low correlations of ECM returns with developed stock market returns to receive substantial diversification benefits (eg. Harvey (1995), Li et al. (2003)). It is also possible that the higher average stock returns in ECM compared to developed market stock returns (eg. Bekaert and Harvey (1997)) may be profitably exploited, though at the expense of higher risk. Moreover, it may be possible to take advantage of the higher persistence documented for ECM returns (see,

for instance, Bekaert and Harvey (1997)) by designing appropriate trading strategies to enhance the profitability of emerging market investments.

Our interest in ECM is therefore a consequence of the increasing value of these markets to the international investor and portfolio manager. Despite the significance of ECM, the existing literature has yet to provide an adequate description of the statistical returns generating process in ECM, while much more is known about developed markets: The general consensus is that advanced stock markets can be adequately described by low order autoregressive in-the-mean processes with time-varying volatility dynamics. There are theoretical reasons why one may expect apriori return dynamics to differ in ECM: Market thinness and nonsynchronous trading biases may be more severe in ECM, given their low level of liquidity (De Santis and Imrohoroglus (1997)). Also, investors tend to react more gradually to new information than investors in developed markets (Barkoulas et al. (2000)). It is thus possible that unlike developed market returns, ECM returns exhibit long memory effects in the conditional mean, with far-reaching implications for asset pricing, risk management and portfolio allocation. There is only very limited evidence to this effect in the existing literature (Barkoulas et al. (2000) and Wright (2001) provide some evidence in favor of long memory in ECM) probably as good-quality, relatively long, data sets on ECM are hard to come by.⁷ In particular, we are aware of no prior study than the present thesis which attempts to provide a more complete characterization of the returns generating process (using only historical price data) in the markets of Asia and Latin America.⁸ Moreover, motivated by the paper of Brock et al. (1992), we use bootstrap simulations of the “favorite” specification of the returns generating process in concert with trading rules, to evaluate, among others, the appropriateness of our modeling

⁷Most prior studies on emerging markets employ monthly, or at best, weekly data obtained from the International Finance Corporation (IFC).

⁸De Santis and Imrohoroglus (1997) model the returns generating process in ECM as AR(1)-GARCH(1,1) processes while Edwards et al. (2003) investigate AR(1), AR(1)-GARCH(1,1), and AR(1)-EGARCH(1,1) specifications. All the aforementioned models are nested in our ARFIMA-FIGARCH framework excluding the EGARCH(1,1) specification for the conditional volatility.

framework for the emerging stock market indices in question.

Particularly attractive is the prospect of uncovering unexploitable deposits of steady streams of profits, more so in markets where the process of integration with the world economy has not yet been completed to alleviate any alleged market “inefficiencies”. With little evidence in favor of the profitability of trading rules in advanced stock markets, especially in the presence of transaction costs, any evidence to the contrary in the markets covered in chapter 3 will provide an interesting basis for comparison. The use of trend-following rules in the context of ECM is primarily motivated by the findings of persistence in ECM returns. There has been some evidence in favor of the forecasting ability of trading rules for a group of Asian markets in Bessembinder and Chan (1995), and even suggestions of profitability for some Asian and Latin American markets in Ratner and Leal (1999). Though the aforementioned studies cover the markets included in Chapter 3 of this thesis, apart from Indonesia, they apply to periods over which these markets were relatively “closed” to international investments, with data running only to the mid-1990s. If one is interested in the feasibility of trading strategies to international investors, one must employ data sets that accurately reflect investable opportunities.

We have chosen to study markets from Latin America and Asia not only because data are more readily available for these ECM, but also because the two regions differ in their degree of “openness”: The Latin American countries in our sample - excluding Chile - opened up to foreign investment earlier and far more extensively than their Asian counterparts, being almost completely open to international investments by or close to the beginning of the sample period (January 1988). The Asian markets were still relaxing gradually foreign ownership restrictions during the course of the 1990s. If international integration translates to more competition and a move towards market efficiency, it would be interesting to evaluate whether the predictability and profitability of the same trading rules applied in all markets exhibit a different pattern of results between the two regions.

1.7.3 Motivation for the Third Research Project (Chapter 4)

Chapter 4 evaluates predictability in stock prices from the perspective of a trading strategy designed to exploit a perceived market anomaly. To this end, a new, direct approach for testing market efficiency is employed, developed by Hogan et al. (2004). This methodology determines whether the trading profits of persistent anomalies constitute statistical arbitrage (SA) opportunities, and is particularly suited to long-term market anomalies as SA is defined over an infinite investment horizon.

Tests of market efficiency, and in particular long-term return anomalies, have long been confounded by the joint hypotheses problem: to test whether there is an inefficiency, one must know what “normal” returns should be, and whether the actual returns deviate from this benchmark. Because theoretically motivated asset pricing models have little corroborating empirical support, there is no consensus on how to measure long-term abnormal returns. According to Fama (1998), this critical caveat limits our ability to confidently reject market efficiency despite the numerous empirical challenges such as the profitability of momentum and value strategies. The approach developed by Hogan et al. (2004) circumvents the joint hypothesis dilemma since the definition of SA is independent of any equilibrium model and, as with standard arbitrage opportunities, its existence contradicts market efficiency.

Fama (1998) also argues that long-term anomalies appear sensitive to the statistical methodology utilized, and in particular expresses concerns over the ability of single t-tests on risk-adjusted alphas to lead to rejections of the EMH. Empirical tests of SA require assumed trading profit dynamics and are in fact combined tests of sub-hypotheses imposing a constraint on the trading profit parameters (mean and volatility). Thus multiple t-tests are required to test for SA. In contrast, the traditional market efficiency literature involves an equilibrium model and a subsequent statistical test, with the equilibrium model being a maintained assumption that is not explicitly tested.

In addition, Hogan et al's (2004) development of the SA methodology has the advantage of monitoring the risk profile of the market anomalies strategies. Most importantly, a trading strategy's probability of making a loss can be calculated at specified investment horizons, providing additional insights into its ability to eventually produce arbitrage profits. This is particularly significant in view of the concerns expressed by Shleifer and Vishny (1997) with respect to "risky arbitrage".

Hogan et al. (2004) study the momentum and value market anomalies in the US and conclude in favor of SA opportunities, implying a rejection of the EMH. Given the significant contribution of their study to the market anomalies and EMH literature in general, both from a conceptual and methodological point of view, it is imperative that further tests of other market anomalies are undertaken to re-evaluate the EMH more confidently. It is also necessary and interesting to gauge the robustness of SA findings by testing market anomalies for SA in markets other than the US.

Chapter 4 merges our interest in dividend policy with an assessment of whether the instigation of trading strategies which aim to profit from "extreme" dividend announcements in the UK market, such as dividend initiations (including dividend resumptions) and dividend omissions, constitute SA opportunities. The attractiveness of the dividend policy lies in the fact that the dividend decision is one of the three major categories of corporate long-term financial decisions that a firm's management has to face. Management can affect shareholder wealth through capital investment, capital structure and dividend decisions. The investment decisions of the firm determine the level of future earnings and future potential dividend. Secondly, capital structure influences the cost of capital which determines, in a way, the accepted investment opportunities. And thirdly, dividend policy influences the amount of equity in the capital structure of the firm through retained earnings; as a consequence it also influences the cost of capital. Allen and Michaely (1995) strengthen the importance of dividends noting that theories of asset pricing, capital struc-

ture, mergers and acquisitions, and capital budgeting, all rely on a view of how and why dividends are paid.

Numerous studies explore the impact of dividend announcements around the announcement day. However, only a handful of academic papers investigate the long-term impact on stock market performance of dividend announcements; and, to the best of our knowledge, only one study - Michaely et al. (1995) - touches upon the construction of trading strategies to exploit abnormal performance relative to the market following dividend announcements, even in a US context. However, the purpose of Michaely et al. (1995) is to robustify their excess returns calculations following dividend initiations and omissions, and do not attempt to investigate whether the strategies represent real investment opportunities. Moreover, they do not explore the performance of the strategies over different investment horizons. The third research project, motivated by some findings of long-term abnormal returns following “extreme” changes in dividend policy (see Michaely et al. (1995) and Boehme and Sorescu (2002)), fills this void in the literature in the context of SA. Trading strategies are constructed to exploit suspected long-term positive price drifts after dividend initiations/resumptions and negative price drifts following dividend omissions. The study incorporates transaction costs and evaluates the feasibility of the trading strategies both in terms of profitability as well as of the risk profile and the probability of making a loss.

We choose to focus on the UK market as, despite its significance in the financial world, virtually no work, to the best of our knowledge, has been done in the area of long-term price reactions after dividend announcements. Comparison with results from the US is warranted. The application of the SA methodology of Hogan et al. (2004) in the UK market reveals whether this market adjusts efficiently to such corporate events.

1.8 The Significance of the Thesis

We will point out the research significance and main contributions to the existing literature of each of the three self-contained projects separately.

1.8.1 Contributions of Chapter 2

- The study maintains the same modeling philosophy of previous research and replicates major empirical findings, such as the U-shaped pattern of Fama and French (1988) in returns autocorrelations.
- The choice of a continuous-time framework renders the notion of the investment horizon at least theoretically irrelevant, and attempts to rescue the confusion in the literature arising from the different specifications of the “holding time period” in stocks over which mean reversion is obtained.
- The methodology developed allows mean reversion in stock prices to arise not as a result of testing over the “appropriate” investment horizon, but rather as an “intrinsic property” of the underlying model for equity prices. This is consistent with the interest rate literature (eg. Hull and White (1993)) and the commodities literature (eg. Schwartz and Smith (1997)).
- Exact discrete-time formulae are obtained for the parameters of the continuous time stock price model without relying on crude approximations of the continuous time stochastic process, thus avoiding temporal aggregation biases. Since estimation of discretized versions of continuous-time models is primarily carried out with high frequency data, there is no need to employ time series with very long span and use overlapping data which bias the coefficient estimates.
- The methodology is particularly suited for pricing index options in a mean-reverting

framework, since not only the mean-reverting parameter but also the volatility parameters are estimated from daily data.

- The existence of mean reversion in the G-7 national stock markets is investigated over a more recent time period of twenty years (1982-2002) and results are compared with existing studies.

1.8.2 Contributions of Chapter 3

- For the first time in the literature, the general parametric ARFIMA-FIGARCH model, which nests a host of specifications and allows for long memory in both the conditional mean and variance, is employed to describe returns processes in ECM. The double long memory model in the context of ECM is theoretically motivated.
- Bootstrap simulations of the estimated returns model together with the application of trading rules on the simulated series to draw conclusions regarding both the robustness of the actual trading outcomes, and the choice of the modeling framework, is for the first time applied in the context of ECM.
- A novel data set of daily MSCI stock price indices for the emerging markets under scrutiny is employed which accurately reflects international investable opportunities in the specific markets. Results on the forecasting ability and profitability of trading rules have direct implications for the interested investor.
- New empirical evidence is added to the literature regarding the forecasting ability and profitability of technical trading rules in ECM, focussing on the market liberalization period. It is confirmed that, in contrast with inferences from developed market studies, it is not imperative to employ very long data series to uncover the predictive capabilities of trading rule signals.

- The robustness of the trading rule results to microstructure biases and to the Asian crisis is evaluated. In particular, Chapter 3 examines whether any predictability/profitability observed during the sample period is merely driven by the negative return outliers occurring during the mid-late 1990s Asian crisis, that may have been correctly picked up by the trading rules.
- The “double-or-out” strategy to exploit technical trading rule signals which has been widely applied in developed market studies is now evaluated in ECM as well. Results can be compared and conclusions drawn regarding the weak form efficiency of ECM.
- The fact that we deal with markets from two geographical regions with differing “degrees” of market liberalization allows inferences on which type of markets technical analysis is bound to be most useful.

1.8.3 Contributions of Chapter 4

- For the first time in the literature, trading strategies are constructed to evaluate and take advantage of abnormal price behavior following dividend initiations and omissions in the UK market. The study reveals whether such an anomaly exists in the first place in the UK market by trying to exploit it profitably, and facilitates comparison with US studies.
- The feasibility and profitability of long-term dividend anomalies trading strategies over different investment horizons and after incorporating transaction costs is evaluated for the first time.
- The results open up new investment opportunities to long-term investors and provide valuable information regarding the riskiness of the strategies and probability of making a loss at specified investment horizons.

- The novel SA test of Hogan et al. (2004) is applied to an anomaly pertaining to corporate announcements (while Hogan et al. investigate primarily momentum and value strategies), significantly so in a market other than the US.
- The methodology of Hogan et al. (2004) is improved by explicitly incorporating serial correlation in trading profits to avoid inappropriate standard errors.

1.9 Organization of the Thesis

The rest of the thesis is divided into three self-contained projects that attempt to model and exploit, from different points of view, predictable patterns in historical price series. Chapter 2 includes a literature review on the modeling of mean reversion in equity prices, proposes a methodology to model “intrinsically” the property of mean reversion, derives testable implications and evaluates them using equity index data for the G-7 economies. Chapter 3 investigates the returns generating process in eight ECM from Latin America and Asia and assesses the profitability of popular trading rules and the suitability of the modeling framework using a bootstrap methodology. Chapter 4 discusses SA as is understood by practitioners and as defined in very recent academic papers, and constructs trading strategies involving dividend initiations and omissions in the UK to test for SA opportunities, and thus market efficiency. Chapter 5 summarizes, discusses the results, and suggests directions for future research.

Chapter 2: Mean Reversion in Equity Prices: The G-7 Evidence

2.1 Introduction

Mean reversion in stock prices still remains a rather controversial issue. Whereas theoretical justifications for the departure from the random walk model of equity prices have proliferated¹, the empirical evidence remains mixed and confusing. Fama and French (1988) and Poterba and Summers (1988) are the first to document the existence of negative correlation² between US equity portfolio returns over “medium” to “long” investment horizons, while Lehmann (1990) finds evidence in favor of return reversals in “winner” and “loser” portfolios even at the weekly frequency. On the contrary, Lo and MacKinlay (1988) report weak positive correlation between US portfolio returns over “short” investment horizons. Kim, Nelson, and Startz (1991) argue that the mean reversion results of Fama and French and Poterba and Summers are only detectable in prewar US data. In turn, Richardson and Stock (1989) and Richardson (1993) report that correcting for small-sample bias problems could reverse the Fama and French and Poterba and Summers results.

Another strand of the literature deals with relative mean reversion in stock index

¹See, for example, the “fad variables” model of Shiller (1981, 1984) and Summers (1986), the “bandwagon effect” explanation of Poterba and Summers (1988), the “over-reaction” hypothesis of De Bondt and Thaler (1985, 1987), the “time-varying risk premium” explanation of Conrad and Kaul (1989), Conrad, Kaul and Nimalendran (1991), Fama and French (1988), and Keim and Stambaugh (1986), the information related (Hasbrouck (1991)) or strategic trading (Admati and Pfleiderer (1989)) market microstructure models, the “institutional structures” framework of Bessembinder and Hertzel (1993), and the “over-reaction and/or partial adjustment to new information” models of Brock, Lakonishok and LeBaron (1992), Jegadeesh (1990), Lehmann (1990), and Lo and MacKinlay (1990a).

²Mean reversion implies that shocks to prices are temporary, i.e., returns are negatively autocorrelated at certain horizons.

data. Kasa (1992), in a multi-country study, reports that national stock indices are cointegrated and share one common stochastic trend which implies that the value of a properly weighted portfolio of shares in the markets of at least two countries that he examines is stationary, and thus will display mean reversion. Richards (1995) criticizes Kasa's results on the grounds that the use of asymptotic critical values in the cointegration tests is not appropriate. However, he detects a stationary component in relative prices of 16 OECD countries which implies relative mean reversion and reports that country specific returns relative to a world index are predictable. Finally, Balvers et al. (2000) report strong evidence of mean reversion over "long" investment horizons in relative stock index prices of 18 countries. Campbell et al. (1997) summarize the debate concisely: "...we simply cannot tell " (p. 80).

The main objective of this chapter is to attempt to "tell" more confidently about the existence of mean reversion in stock prices: Whilst maintaining the spirit and modeling assumptions of previous methodologies (in particular, Fama and French's (1988) approach), we aim to show that if the "intrinsic" behavior of stock prices is examined, which clearly was missing from earlier studies, then a reconciliation of the mixed empirical evidence is possible. Our motivation stems from a number of important points that emerge from the relevant literature: First, in contrast with the interest rate literature, mean reversion in stock prices arises as a result of the specification of different investment horizons, rather than as an intrinsic property of the underlying stochastic model of equity prices. In their vast majority, the methodologies employed to examine mean reversion involve the use of a particular function of the sample autocorrelations between returns over different investment horizons. However, the theoretical justification of serial correlation in stock returns rests upon a number of theories (see footnote 1 and Section 2.2.3 for more details) which try to explain the various patterns in returns autocorrelations not in terms of the holding period, but as a result of the interaction between underlying economic factors. Moreover,

the existing methodologies imply that the statistical properties of the underlying time series are a function of the investment horizon, which makes the detection of mean reversion a rather arbitrary issue. Second, a consequence of testing for mean reversion by returns autocorrelation tests is that long time series need to be employed. As Balvers et al. (2000) put it, “a serious obstacle in detecting mean reversion is the absence of reliable long time series, especially because mean reversion, if it exists, is thought to be slow and can only be picked up over long horizons.” (p. 746).

In order to overcome these shortcomings Chapter 2 develops a two-factor continuous time model of stock prices that allows mean reversion and uncertainty in the equilibrium level to which prices revert. On theoretical grounds, this model is consistent with many of the proposed explanations of mean reversion in stock prices, such as “the over-reaction” hypothesis, the “bandwagon effect”, the “time-varying risk premium”, etc. On empirical grounds, the choice of a continuous time framework attempts to rescue the confusion in the literature arising from the specification of the “holding time period” in stocks, a notion which becomes at least theoretically irrelevant in a continuous time setting. In other words, we are able to detect mean reversion as an “intrinsic” property of the underlying model for equity prices, that is, without explicit reference to the investment horizon over which price changes are measured. This obviates the need for employing long time series; in fact an advantage of our approach is that the recovery of the continuous-time parameters from discrete data sets can be achieved even from relatively small samples. Our continuous time model is tested in the G-7 national stock markets, US, UK, Japan, France, Canada, Germany, Italy, and is empirically supported. Finally, nesting mean reversion explicitly within the underlying stochastic process and thereby estimating the continuous time parameters directly from observables could be used for the more accurate valuation of equity derivatives in the spirit of Lo and Wang (1995), and the development of new trading strategies (for capitalizing on mean reversion) - possibly “contrarian”-, in

the spirit of DeBondt and Thaler (1985), Richards (1995, 1997), and Balvers et al. (2000).

The maintained hypothesis is that the state variable, i.e., the (log) stock price is a difference stationary process in the spirit of Nelson and Plosser (1982). This approach was used by Fama and French (1988) and Poterba and Summers (1988) in their pioneering discrete-time models. Our continuous time framework assumes that (log) stock prices are generated by the mix of a nonstationary component modeled as an Arithmetic Brownian motion, and a stationary component modeled as an Ornstein-Uhlenbeck stochastic process. We recover the continuous time parameters, assess their statistical significance, and demonstrate that the mean reversion of the stationary component causes predictability even in daily stock returns which is opposed to the effect of the nonstationary price component which produces white noise in the continuously compounded returns.

The remainder of the chapter is organized as follows. In section 2.2 we present a review of the literature on mean reversion in stock returns and discuss the major empirical findings. In section 2.3 we present our two-factor continuous time stock price model, and develop reduced form expressions of the slope coefficients that embody the continuous time parameters without relying on crude approximations of the continuous time stochastic processes, thus avoiding temporal aggregation biases. In section 2.4 we show how the model can be tested and we propose a simple way to identify the continuous time parameters. Section 2.5 presents the data and our empirical results. Finally, Section 2.6 concludes the chapter.

2.2 Literature Review

2.2.1 Correlation/Regression and Variance Ratio Tests

The extent to which stock prices exhibit mean-reverting behavior is crucial in assessing assertions such as Keynes's (1936) "that all sorts of considerations enter into market

valuation which are in no way relevant to the prospective yield” (p.152). If market and fundamental values diverge, but the differences are eventually eliminated by speculative forces, then stock prices will revert to their mean. Returns must be negatively serially correlated at some frequency if “erroneous” market moves are to be corrected. However, although the presence of negative correlation may signal departures from fundamental values, it could also arise from variation of risk factors over time.

The early literature on market efficiency summarized by Fama (1970) dismissed findings of autocorrelation in short horizon (daily and weekly) returns as being of no economic significance and thus indistinguishable from a random walk. Therefore, this early work largely concluded that the market is efficient. French and Roll (1986), using a dataset for all common stocks listed on the New York and American Stock Exchanges between 1963 and 1982, found that daily returns of individual securities are slightly negatively autocorrelated, albeit significantly so. They attribute this evidence to trading noise rather than measurement errors due to bid-ask biases in close-to-close returns. Other work also focusing on short horizon returns (Fama and Schwert (1977), French et al. (1987)) arrived at the conclusion that predictable variation is a small part (usually less than 3 percent) of the variation of returns.

Shiller (1984) and Summers (1986) challenge the above interpretation of autocorrelations in short horizon returns. They present simple models of inefficient markets in which prices take large, slowly decaying swings away from their fundamental values, which are caused by “fads” or irrational bubbles. Summers (1986) showed that if a fads component such as this accounted for a large fraction of the variance of returns, the fads behavior might be difficult to detect by looking at short horizon autocorrelations of returns as those early tests had done. The intuition behind Summer’s reasoning was that if stock prices took large jumps away from their “fundamental” values, and then only reverted back towards the fundamental price over a period of years, the autocorrelations of daily,

weekly, or even monthly returns would capture only a small fraction of this mean reversion. Short-horizon tests simply lack the power to detect a slow mean-reverting price component.

Summers (1986) translated the “fads” hypothesis into the statistical hypothesis that prices have slowly decaying stationary components. This modeling approach was utilized by Fama and French (1988) in their seminal paper which produces evidence against the long-held view that stock prices follow a random walk, using long-horizon regressions of multi-year returns on past multi-year returns. Fama and French model the natural log of a stock price at time t as the sum of a random walk (nonstationary) component $q(t)$ and a stationary component $z(t)$:

$$p(t) = q(t) + z(t) \tag{2.1}$$

and

$$q(t) = q(t - 1) + \mu + \eta(t) \tag{2.2}$$

where μ is the expected drift and $\eta(t)$ is white noise. As in Summers (1986), the stationary component is modeled as a first-order autoregressive process (AR1):

$$z(t) = \phi z(t - 1) + \varepsilon(t) \tag{2.3}$$

where $\varepsilon(t)$ is a white noise error process uncorrelated with $\eta(t)$, and ϕ is a constant close to but less than 1.0. Thus the general hypothesis in the Fama and French (1988) model is that stock prices are nonstationary processes in which the permanent gain from each period’s price shock is less than 1.0; the temporary part of the shock will be gradually eliminated, and will play no long-run role in determining asset values. However, a significant mean-reverting temporary part implies predictability (in the form of negative correlation) of stock returns. The authors show that a U-shaped pattern in the slopes of returns autoregressions may theoretically be expected in their modeling framework.

They test this prediction using continuously compounded monthly real returns data on New York Stock Exchange (NYSE) stocks for the period 1926-1985. Industry portfolios of equally weighted stocks are formed, classified on the basis of size, and monthly data are summed to get overlapping monthly observations on longer horizon returns. Their results indeed suggest a U-shaped pattern of slopes, starting at around zero for successive yearly returns, ranging between -0.30 and -0.45 for 3 to 5 year returns, and then moving back towards 0.0 for longer return horizons. Predictable return variation due to mean reversion is thus between 30 percent and 45 percent of the variances of 3-5 year returns. In other words, prices seem to possess a significant transitory component. Fama and French recognize that their evidence suffers from statistical imprecision, mainly due to spurious serial correlation induced by the overlap of monthly data in long-horizon returns, as well as due to problems of changing parameters such a long time period implies. Also, the bias increases with the return horizon since effective sample sizes are smaller and the overlap increases. To adjust for the positive correlation in the residuals induced by overlapping observations Fama and French calculate standard errors by the method of Hansen and Hodrick (1980). They also adjust for downward bias in the OLS estimates of the slopes by Monte Carlo experiments. They find that the unadjusted slopes have little bias, being slightly bigger in absolute value than their bias-adjusted counterparts.

A closely related approach to the regression test to study serial correlation in multiperiod returns is the variance ratio test. Both of these methodologies involve using a particular function of the sample autocorrelations to test the hypothesis that all autocorrelations equal zero. The variance ratio test exploits the fact that if stock prices follow a random walk, the return variance should be proportional to the return horizon. Cochrane (1988) shows that the q -period variance ratio statistic satisfies the relation:

$$VR(q) = \frac{Var[r_t(q)]}{qVar[r_t]} = 1 + 2 \sum_{k=1}^{q-1} \left(1 - \frac{k}{q}\right) \rho(k) \quad (2.4)$$

where $r_t(k) = \sum_{i=0}^{k-1} r_{t-i}$, r_t denoting the continuously compounded return in month t , and $\rho(k)$ is the k -th order autocorrelation coefficient of the sequence of returns $\{r_t\}$. In other words, $VR(q)$ is a linear combination of sample autocorrelation coefficients with linearly declining weights. This statistic converges to unity if returns are uncorrelated through time. If some of the price variation is due to transitory factors, however, autocorrelations at some lags will be negative and the variance ratio will fall below one. Conversely, variance ratios exceeding unity suggest the presence of positive return autocorrelation.

Lo and Mackinlay (1988) derive the formal sampling theory of the $VR(q)$, refine it for power and bias, and correct it for heteroskedasticity to yield an asymptotically standard normal test statistic. The authors compute the “refined” variance ratio estimator for weekly data and aggregation intervals $q = 2, 4, 8, 16$. The data set consists of NYSE-AMEX (American Stock Exchange) stock returns from September 6, 1962, to December 26, 1985, aggregated in equal-weighted and value-weighted indices. The choice of weekly data was due to their sampling theory being based wholly on asymptotic approximations, thus requiring a large number of observations. Daily sampling was not preferred because of the biases associated with non-trading, the bid-ask spread, nonsynchronous prices, etc., which are mitigated in weekly data. Their findings suggest that the random-walk model can be rejected for weekly data at all the usual significance levels for the entire time period and the two equal sub-periods in which they split the sample, particularly in the case of the equal-weighted index.³ Variance ratios are larger than 1, rising with the aggregation interval q , even though their significance declines with rising q . The results suggest the existence of positive serial correlation in weekly holding-period returns. In particular, for

³Lo and Mackinlay (1989) use Monte Carlo simulations to examine the power of the variance ratio test against different alternatives to the null of the random walk. Under an AR(1) representation for $\{r_t\}$, the power of the variance ratio test varies over the period of differencing (q), initially rising with q , then falling. Yet for all values of q , the power of the variance ratio test exceeds that of the Box-Pierce Q-statistic, but not the Dickey-Fuller test for a unit root. When the alternative model to the null of a random walk is a random walk plus a stationary component in returns, the variance ratio has higher power than alternative tests, for all but very high values of q ($q > 32$), in a sample of 1034 computer generated observations.

$q = 2$, a variance ratio equal to 1.30 implies that the first-order autocorrelation for weekly returns is about 30%. Size-sorted portfolios (portfolios of both small and large firms) also exhibit positive serial correlation at weekly holding periods, but individual securities show variance ratios less than one, implying negative serial correlation at the weekly frequency, albeit insignificant. These results complement French and Roll's (1986) finding that daily returns of individual securities are slightly negatively autocorrelated. The authors develop a model of infrequent – or nonsynchronous - trading to check whether artificial positive serial correlation is impounded to the equal-weighted index of stock returns by the fact that small capitalization stocks trade less frequently than larger stocks.⁴ They find that these large autocorrelations cannot be attributed solely to the effects of infrequent trading. Finally, they note that a combination of infrequent trading and Roll's (1984) bid-ask effect may explain a large part of their finding of small negative autocorrelation in individual stock returns.

Although the above results are inconsistent with the random walk hypothesis, they hold little comfort to the adherents of the mean reversion hypothesis as discussed by Summers (1986), Fama and French (1988), and Poterba and Summers (1988). The latter authors employ Summers' model to test for transitory components in stock prices. Their analysis is based on monthly returns on NYSE stocks from the CSRP database between 1926-1985. Using variance ratio tests, they find evidence of positive, statistically significant, serial correlation at horizons shorter than a year, but negative return autocorrelation at longer horizons for both the equal- and value-weighted index. Since the analysis is based on monthly returns, the authors argue that findings of positive serial correlation are not likely to be due to infrequent trading. Thus, the Poterba and Summers results parallel those of Lo and Mackinlay (1988) for short horizons, and those

⁴The common intuition is that new information is impounded first into large-capitalization stock prices and then into smaller-stock prices with a lag. This lag induces positive serial correlation in, for example, an equal-weighted index of stock returns. Ofcourse, this induced positive serial correlation would be less pronounced in a value-weighted index.

of Fama and French for long investment horizons. Poterba and Summers also provide international evidence from 17 other equity markets which, by and large, confirm the presence of transitory components in stock prices, with returns showing positive autocorrelation over short periods (less than a year) and negative autocorrelation over longer periods. It should be noted that unlike Lo and Mackinlay, Poterba and Summers do not rely on asymptotic statistical tests, but calculate standard errors for the variance ratios using Monte Carlo experiments under the null hypothesis of serially independent returns, assuming normal disturbances. Although the simulated evidence suggests that variance ratio tests are more powerful than first-order autocorrelation tests, they still have little power to detect persistent, but transitory, return components, even in the NYSE sample consisting of monthly data for a 60-year period! A sensible balancing of Type I and Type II errors suggests using critical values above the conventional 0.05 level, which increases the significance of the mean-reversion results.

Subsequent research criticized the evidence reported using variance ratio and autoregression statistics on statistical grounds. Kim et al. (1991) used randomization methods to estimate the unknown sampling distributions of both types of statistics, the advantage being that no assumptions are made with this approach regarding the underlying unknown distribution of stock returns. The results suggest that significance levels are much lower (and standard errors higher) than previously reported. Employing both multiperiod autoregression and variance ratio tests and the Fama and French (1988) and Poterba and Summers (1988) samples, Kim et al. are able to confirm the aforementioned authors' results for the whole sample period, but note that evidence in favor of mean reversion disappears if one considers only data after World War II.

More importantly, there are several difficulties with long-horizon inferences which could stem from the fact that when the horizon q is large enough relative to the total time span ($T = nq$), where n represents sample size, asymptotic distribution theory

provides a poor approximation to the sampling distribution. A commonly recognized feature of variance ratio and autocorrelation statistics is that even though the sample may be large, the number of non-overlapping observations can still be small. This implies that there is not much independent information in a long-time series of multiyear returns, which is an additional factor why conventional large sample approximations to sampling distributions, under the null of independently distributed returns, can perform poorly in practice. The important question that then arises is whether mean reversion evidence can be attributed to a slowly decaying component of stock prices or to the poor performance of asymptotic theory in small samples.

Richardson and Stock (1989) provide an alternative asymptotic analysis in which the degree of overlap in the data is allowed to increase with the sample size, rather than being fixed as in conventional asymptotic theory. They find that the variance ratio statistic has a limiting chi-squared distribution if non-overlapping data is used, while with overlapping data it converges in distribution to a random variable that is a functional of Brownian motion. In this framework, the variance ratio has an expected value of 0.751 with a return horizon of 60 months and a sample period of 60 years, despite the independent increments (random walk) null hypothesis. The multiyear autocorrelation statistic also has a limiting distribution in terms of functionals of Brownian motions. Under weak assumptions, involving various forms of heteroskedasticity, the limiting distributions of the two statistics do not depend on any unknown parameters, and therefore, their asymptotic distributions under the null hypothesis that returns are unpredictable can be approximated by monte carlo methods. Richardson and Stock re-evaluate the evidence in Fama and French (1988) and Poterba and Summers (1988) to find that adjusting for small sample sizes results in substantially fewer rejections of the random walk hypothesis. In particular, the evidence in favor of mean reversion is much less pronounced using the asymptotic values of Richardson and Stock.⁵

⁵For example, the Fama-French (1988) procedure leads to 19 rejections of the null since 19 out of the

Richardson (1993) examines the above point in more detail. He argues that autocorrelation estimates and corresponding serial correlation patterns (such as the U-shaped pattern documented by Fama and French (1988)) should be expected even from random walk data. This is due to the combination of two effects. First, over the vector of multiperiod autocorrelation estimates, some estimates will differ from their random-walk expected value of zero. Order-statistic theory suggests that these differences can be quite large. Monte Carlo simulations produce an average value of 0.35 for the autocorrelation estimator across different investment horizons. Second, estimation with overlapping data causes multiperiod autocorrelation estimators of similar holding period returns to have many sample autocovariances in common, thus picking up much of the same spurious autocorrelation. Instead, if two estimators are far apart in terms of the investment horizon they refer to, then they have little in common and should be close to their unconditional average of zero. Richardson employs the variance-covariance matrix of serial correlation estimators developed by Richardson and Smith (1991), and using the Wald statistic of joint significance for the slope coefficients in returns autoregressions for all the holding periods and portfolios (a total of 29) looked at by Fama and French, reports only one deviation from the random walk model. His results appear valid even after accounting for heteroskedasticity.

2.2.2 Tests of Relative Mean Reversion

Another strand of the literature deals with relative mean reversion in stock index data. In these types of tests, a fundamental or trend path for the series under investigation does not need to be specified. Kasa (1992) finds that national stock indexes of Canada, Germany, Japan, the United Kingdom, and the United States are cointegrated and share

96 bias-adjusted slopes in returns autoregressions are two Hansen-Hodrick (1980) standard errors away from zero. Using the asymptotic p values of Richardson and Stock (1989) results in 3 rejections of the null rather than 19.

one common stochastic trend. The implication of this result is that the value of a properly weighted portfolio of shares in the markets of at least two countries is stationary and thus will display mean reversion. Richards (1995) criticizes Kasa's results on the grounds that his use of asymptotic critical values in the cointegration tests is not appropriate. When finite-sample critical values are employed, however, Richards finds no significant evidence of cointegration among a group of 16 OECD countries, containing the five countries in Kasa's sample. Interestingly, he detects a stationary component in relative prices (implying partial mean reversion) and reports that country-specific returns relative to a world index are predictable. Accordingly, Richards (1997) implements the "contrarian" strategy developed by De Bondt and Thaler (1985) to exploit (partial) mean reversion across 16 national stock markets using monthly data between 1969 and 1995. He documents "winner-loser" reversals which are strongest around the 3-year horizon and return differentials averaging more than 6 percent per annum, indicating negative autocorrelation in returns "between" markets.

Balvers et al. (2000) employ a panel data approach, and using the additional cross-sectional power gained from national stock index data of 18 advanced economies between 1969 to 1996, find significant evidence of full mean reversion in national equity indices relative to a reference index. Their findings imply a significantly positive speed of reversion with a half-life of three to three and one-half years, under the assumption that the speeds of reversion in different countries are similar. Further support for the robustness of their mean reversion findings is provided by parametric contrarian investment strategies that fully exploit mean reversion across national stock indexes and outperform a buy-and-hold and a random-walk-based strategy.

2.2.3 Theoretical Justifications and Further Empirical Evidence

2.2.3.1 Fads or Irrational Bubbles

The “fads” - or irrational bubbles - explanation for mean reversion has been proposed by Shiller (1984) and Summers (1986) and translated into the statistical hypothesis that prices have slowly decaying stationary components. This modeling approach was exploited by Fama and French (1988) and Poterba and Summers (1988) in their multi-year regression and variance ratio tests respectively. The idea is that fads cause prices to take large, slowly decaying swings away from their fundamental values, and then only revert back to the fundamental price over long horizons. This explanation is associated with inefficient markets.

2.2.3.2 Time-Varying Risk Premium

Conrad and Kaul (1989), Conrad et al. (1991), Keim and Stambaugh (1986) and Fama and French (1988) argue that predictability in long horizon returns can result from time-varying equilibrium expected returns generated by rational pricing in an efficient market. Expected returns correspond roughly to the discount rates that relate a current stock price to expected future dividends. In particular, Fama and French present a hypothetical scenario in which shocks to expected returns are uncorrelated with shocks to rational forecasts of dividends. Then a shock to expected returns has no effect on expected dividends or expected returns in the distant future, and thus no long-term effect on expected prices. This implies that the cumulative effect of a shock on expected returns must be exactly offset by an opposite adjustment in the current price. In this scenario, autocorrelated equilibrium expected returns lead to slowly decaying components of prices that are difficult to distinguish from the temporary price components of an inefficient market.

Ball and Kothari (1989) actually investigate the issue of whether serial autocorrelation in asset returns is due to asset mispricing (with the consequent implication of market

inefficiency) or due to changes in the risk properties of securities. They argue that mean reversion in stock prices may simply reflect the natural change in a company's risk properties, in response to leverage changes brought about by variations in return on equity. By allowing for time-varying betas in a CAPM framework they find that 97.4% of the variation in returns is explained by changes in systematic risk, as proxied by beta.

More support in favor of the rational time-varying risk premium explanation for mean reversion comes from evidence reporting that much of the mean reversion in long time series seems to be concentrated in the month of January (Jegadeesh, 1991), consistent with variations in the risk premia demanded by investors. This is because sales in December of loss-making securities are executed to provide a tax shelter for yearly income, which causes January returns to be unusually high. This explanation is in agreement with the findings of De Bondt and Thaler (1987).

Economic explanations of mean reversion in terms of time-varying risk premia are persuasive when applied to long periods of time, when we might expect economic fundamentals to vary. This accords with findings in the literature of mean reversion at long horizons, but not with negative serial correlation between returns documented at shorter frequencies.

2.2.3.3 The Bandwagon effect

Poterba and Summers (1988) point out that transitory components in stock prices imply variations in ex ante returns. They examine whether variations in ex-ante returns are better explained by changes in interest rates and volatility or as by-products of price deviations caused by noise traders. They use the dividend discount model and assume an AR(1) process for the transitory component to develop expressions which allow calculation of the variation in required returns that is necessary to generate the time series process of observed returns. They find that substantial variability in required returns is necessary to explain mean reversion in prices, which cannot be accounted for by fluctuations in

risk factors. On the other hand, if transitory components are viewed as a reflection of mispricing, they are also large in relation to traditional views of market efficiency. Poterba and Summers support the view that equity demands of noise traders following a moving average process of order one, similar to one of those for required returns which generates the observed (by their study) pattern of positive, then negative autocorrelation in returns, will also generate this pattern in ex-post returns.

2.2.3.4 Strategic Trading

Patterns in intraday expected returns and/or across trading days can occur because of changes in risk levels, settlement procedures, or be induced exogenously by fluctuations in order imbalances when a bid-ask spread is present. However, it is possible that such patterns can emerge endogenously in stationary environments, that is, in situations in which the defining characteristics of all periods are the same. Admati and Pfleiderer (1989) develop a model in which the interactions among potentially informed traders, discretionary liquidity traders, nondiscretionary liquidity traders and one or more market makers lead to patterns in expected price changes. They show that, in their model, a mean reverting pattern in asset returns may arise across trading days, which cannot be considered spurious since the bid-ask bounce occurs as a result of information-based nonsynchronous trading; that is, serial dependence is a result of economic forces rather than measurement error. With respect to the timing of patterns in asset returns, the authors suggest that the end of the trading day is a period of concentrated buying. This causes transaction prices to be biased upwards by the end of the day, and expected price changes to be positive when measured from the midday to the close, but smaller and possibly negative when measured from the close to the next day's opening price.

Bessembinder and Hertzel (1993) investigate return behavior around regularly scheduled periods of nontrading, such as weekends and holidays. They first estimate first-order daily autocorrelations in US equity index returns using 105 years of daily data from 1885

to 1989, and repeat the procedure for 10 subperiods. Additionally, they examine Japanese equity returns, returns of size-ranked equity portfolios and individual equities, as well as returns in 10 US futures markets. They find unusually high, positive and significant correlation between Friday and Monday equity returns across the different markets, contrary to the “weekend effect”, and document a similar phenomenon around holiday closings. The most striking of their findings is that the correlation of returns the second day after a nontrading period (either weekend or holiday) with returns the day after the nontrading period is typically significantly lower than correlations measured at one day lag on other days. In particular, it is negative and significant for most of the return series examined (S&P 500 index, eight out of the 10 futures markets), implying a reversal of price movements. For example, the Tuesday AR(1) coefficient is -0.064 for the S&P 500 index over the whole 1885-1989 period and -0.142 for the S&P equity index futures. Subperiod results suggest the above autocorrelation pattern is fairly consistent over time, while evidence from the Tokyo Stock Exchange indicates that it is not unique to US markets. Moreover, neither firm size appears to be important in determining the autocorrelation pattern around nontrading days, nor the averaging process implicit in index returns, as a similar pattern is detected in individual equity returns (which are also free of the upward bias due to nonsynchronous trading known to exist in portfolio returns). In addition, the price reversal pattern does not appear to be explained by bid-ask bounce; similar results are found for returns computed using the mean of closing bid and ask prices.⁶ Finally, the observed autocorrelations could be due to a pattern in errors with which reported prices measure true prices. However, the most prominent measurement error theory, nonsyn-

⁶Kaul and Nimalendran (1990) present a model which assumes that bid-ask errors are independent across time, inducing a negative serial correlation pattern in returns which converges to a value of 0.5 in the limit. Hence it is possible to produce explanations of the Fama and French (1988) results without recourse to any idea of mean reversion towards fundamental value. Their results from price data on NYSE-AMEX shares for the period 1982-1987 suggest that at least half the variation in daily returns can be explained by bid-ask spread bias, and is thus spurious. Given the discussion above, we believe that although bid-ask spread bias may induce volatility in returns, it is not a sufficient explanation for the apparent mean reversion in stock prices.

chronous trading, appears to be inconsistent with the documented tendency for Tuesday price moves to reverse Monday price moves.

Bessembinder and Hertz (1993) conclude that the observed autocorrelations are due to a pattern in true (transactable) prices, as indicated by the fact that this pattern appears in both spot and future returns. A possible explanation for the findings of this study could lie in models incorporating strategic behavior by market participants, such as the Admati and Pfleiderer (1989) model which allows for price reversals. In any event, any potential explanation cannot rely on a particular market structure as the observed results are quite uniform across specialist and open outcry markets.

2.2.3.5 The Overreaction Hypothesis

De Bondt and Thaler (1985) argue that stock markets overreact to information in past earnings and/or security prices, at the expense of longer-run trends in these variables. That is, agents over-revise their expectations in a Bayesian sense. In particular, De Bondt and Thaler (1987) suggest that the origin of the observed overreaction of stock prices may be an undue sensitivity to more recent news about any given company's performance, especially recent earnings announcements. In their 1987 paper they find earnings are mean reverting and this may explain mean reversion of stock prices for companies in their sample.

As a result of this overreaction to recent information, an investor with a longer-term perspective than is normal can earn systematic profits by buying "undervalued" stocks and selling "overvalued" stocks. De Bondt and Thaler (1985) use monthly data from the US in the period 1926-1982, and for each security in their sample they calculate the 36 month cumulative abnormal return – CAR -, which is the sum of the alphas of each month. They repeat the process 46 times for each of the three-year subsamples of the period 1932-1977 formed by advancing the starting date one year on each occasion. Thus overlapping returns are used once more. The CARs for each of the securities in the sample

are then ranked from highest to lowest and assigned to “winner” and “loser” portfolios. The overreaction hypothesis predicts that following the portfolios formation, the CAR of the winning portfolios will be negative on average, and the CAR of the loser portfolios positive. Thus, according to this hypothesis, if one buys “losers” and holds them for the next few years, financing the strategy by selling “winners”, one will on average make money. They find that loser portfolios outperform the market by, on average, 19.6% in the 36 months after their formation. Winner portfolios lose, by contrast, 5% of their value on average relative to the market. The average CAR of such a contrarian investment strategy is 24.6% over a three-year period, confirming findings of mean reversion over long horizons.

However, most of the reversal activity in the De Bondt and Thaler (1985) sample seems to be concentrated in successive months of January. This suggests a role for tax factors, later confirmed by De Bondt and Thaler (1987) and Jegadeesh (1991). Nevertheless, Chopra et al. (1992) find that cumulative return-based overreaction results are not peculiar to January, since over 50% of the overreaction occurs in non-January months. They also find that a significant degree of overreaction remains in the De Bondt and Thaler (1985) sample, even after adjusting for the impact of the differential size and risk properties of the corporations. The overreaction phenomenon is not simply a re-packaged discovery of the size effect. They do find, however, that the overreaction effect is larger for small firm portfolios, where the shareholding is dominated by individual investors.

Conrad and Kaul (1993) show that long-term contrarian strategies suffer from a methodological drawback which could spuriously inflate their profitability. By cumulating short-term returns over long periods (with the CAR measure), these strategies cumulate not only the “true” short-term returns but also the upward bias in each of the single period returns due to measurement errors in observed prices such as bid-ask errors, nonsynchronous trading, and/or price discreteness. Consequently, Conrad and Kaul em-

ploy the buy and hold metric to measure long-term performance, which greatly reduces the statistical biases inherent in CAR measures, as for all k period returns, the buy and hold measure contains only a constant bias (the bias in a single period's return). This contrasts with k times the single-period return's bias in the cumulative k -period measure. Employing a sample of NYSE firms over the 1926 to 1988 period, they show that all non-January returns to long-term contrarian strategies are eliminated. In contrast to the findings of Chopra et al. (1992), Conrad and Kaul demonstrate that the actual return to an arbitrage portfolio of losers and winners is solely due to January returns, but this "January effect" has no relation to past performance of the securities. Hence, they conclude that there is no evidence of market overreaction.

Other studies have found that short-horizon contrarian strategies consistently make substantial profits, implying that mean reversion is a property of stock prices even at short frequencies. Using monthly stock data for the period 1929-1982, Jegadeesh (1990) finds strong evidence of negative autocorrelation with vector autoregression tests, which he exploits via a suitably devised contrarian trading rule to make abnormal profits of about 2 percent per month. None of the usual controls for size, or shifts in risk, substantially erode this result. As such, the Jegadeesh results suggest that not only does mean reversion exist, but also it allows informed agents to make potentially large profits. Lehmann (1990) investigates the degree of mean reversion in weekly data by examining the profitability of a contrarian trading strategy based on shorting this week's winners and buying this week's losers, and then holding for one week. He finds consistent profits over the period 1962-1986. Although both the Jegadeesh and Lehmann results could be interpreted as evidence of significant stock price overreactions to information, Lo and Mackinlay (1990a) question this inference and argue that the contrarian profits result mainly from some stocks reacting quicker to information than others, leading to a size-related lead-lag effect in stock returns. However, Jegadeesh and Titman (1995) show that most of the contrarian

profit is indeed due to stock price overreaction and a very small fraction of the profit can be attributed to this lead-lag effect.

Finally, a word of caution about the “overreaction literature”. This research seeks to find evidence of systematic price reversals in security markets, in contravention of the random walk hypothesis, without specifying any particular form for the process generating security prices. Hence, while this literature has the benefit of circumventing the need to postulate a particular alternative to the random walk model, it faces the consequent cost of using tests of low power such a generality implies.

In conclusion to the literature review, empirical evidence in favor of mean reversion in stock prices has been uncovered over both “short” and “long” investment horizons, using different data sets over different time periods. With data mining criticisms apparent, we find it imperative to develop a model which nests “intrinsically” the mean reversion property and does not hinge upon the choice of the investment horizon or rely on overlapping data for estimation purposes.

2.3 The Continuous Time Stock Price Model

2.3.1 The Model

Let $p(t)$ be the natural log of a stock price at time t . Following Fama and French (1988), among others, we model $p(t)$ as the sum of a nonstationary component, $q(t)$, and a stationary component, $z(t)$, i.e.

$$p(t) = q(t) + z(t), \tag{2.5}$$

We assume that the permanent component follows an Arithmetic Brownian Motion

(ABM) process:

$$dq(t) = \alpha dt + \sigma dW_1(t), \quad (2.6)$$

where α and σ are constants, and $dW_1(t)$ is a standard Wiener process with mean zero and unit variance.

The temporary component is assumed to follow an Ornstein-Uhlenbeck stochastic process:

$$dz(t) = \beta(\gamma - z(t))dt + \rho dW_2(t), \quad (2.7)$$

where β is the speed-of-adjustment coefficient, γ is the long run mean of the process, ρ is the diffusion coefficient which allows the process to fluctuate around its long-run mean in a continuous but erratic way, and $dW_2(t)$ is a standard Wiener process independent of $dW_1(t)$.

The diffusion process in expression (2.7) is also known as a mean reverting elastic random walk; it is both Gaussian and Markovian but unlike the Wiener process, it does not have independent increments. Furthermore, when $t \rightarrow \infty$ we get an equilibrium stationary distribution. Negative correlation between returns can be explained intuitively as follows: for $\beta > 0$, and $z(t) > \gamma$, we would expect the change in the temporary component of the (log) stock price to be negative. This is clearly because $(\gamma - z(t)) < 0$ and hence the expected change, $E(dz(t))$, must be negative. Similarly, if $(\gamma - z(t)) > 0$, then we would expect that $E(dz(t))$ must be positive. Thus, the process always reverts to the mean γ with speed β . Finally, since $dW_1(t)$ and $dW_2(t)$ are independent Wiener processes, we assume (as in Fama and French (1988)) no correlation between the permanent and stationary components of the (log) stock price.

The general hypothesis in our continuous time stock price model in eq. (2.5)-(2.7) is that stock prices are nonstationary processes in which the permanent gain from each period's price shock is less than 1.0; the temporary shock will be gradually eliminated.

However, a significant temporary part of the shock implies predictability of stock returns.⁷

The solution to eq. (2.6) for $s > t$ is given by:

$$q(s) = q(t) + \alpha(s - t) + \sigma \int_t^s dW_1(\tau), \quad s \geq t. \quad (2.8)$$

The scalar stochastic differential equation in (2.7) is narrow-sense linear and autonomous; its solution is given (see Arnold (1974)) by:

$$z(s) = \gamma + e^{-\beta(s-t)}(z(t) - \gamma) + \rho e^{-\beta(s-t)} \int_t^s e^{\beta(\tau-t)} dW_2(\tau), \quad s \geq t. \quad (2.9)$$

Taking Δ as an arbitrary time step, expressions (2.8) and (2.9) can be written in the following equivalent form:

$$q(t + \Delta) = q(t) + \alpha\Delta + \sigma \int_t^{t+\Delta} dW_1(\tau), \quad (2.10)$$

and

$$z(t + \Delta) = \gamma + e^{-\beta\Delta}(z(t) - \gamma) + \rho e^{-\beta\Delta} \int_t^{t+\Delta} e^{\beta(\tau-t)} dW_2(\tau). \quad (2.11)$$

If we interpret Δ as the time discretization interval, expression (2.11) implies an exact discrete time autoregressive process of order one (AR(1)):

$$z(t + \Delta) = \theta + \varphi z(t) + \epsilon_{t+\Delta}, \quad (2.12)$$

where

$$\theta = \gamma(1 - e^{-\beta\Delta}), \quad (2.13)$$

$$\varphi = e^{-\beta\Delta}, \quad (2.14)$$

⁷ Schwartz and Smith (1997), independently to our work, develop a “Short-Term / Long-Term Model” for commodity prices.

$$\epsilon_{t+\Delta} = \rho e^{-\beta\Delta} \int_t^{t+\Delta} e^{\beta(\tau-t)} dW_2(\tau). \quad (2.15)$$

As in Fama and French (1988), the temporary component in expression (2.12) has an autoregressive structure. The parameter φ captures mean reversion in the temporary component and causes predictability in the form of negative correlation of returns. It is important to note that φ is not a constant but instead varies with any discrete investment horizon and depends explicitly on the intrinsic mean-reverting parameter β .

Since ρ and β are constants and $dW_2(\tau)$ is a standard Wiener process, it follows directly from eq. (2.15) that $\epsilon_{t+\Delta}$ is normally distributed, with mean

$$E(\epsilon_{t+\Delta}) = 0,$$

and variance

$$Var(\epsilon_{t+\Delta}) = \frac{\rho^2}{2\beta} (1 - e^{-2\beta\Delta}). \quad (2.16)$$

It is important to observe that the variance of $\epsilon_{t+\Delta}$ in eq. (2.16) is equal to the conditional variance (as of a generic time t) of the temporary component of the (log) stock price process, $z(t + \Delta)$, given by expression (2.11):

$$Var_t(z(t + \Delta)) = \frac{\rho^2}{2\beta} (1 - e^{-2\beta\Delta}). \quad (2.17)$$

The conditional mean of $z(t + \Delta)$ in eq. (2.11) is given by:

$$E_t(z(t + \Delta)) = \gamma + e^{-\beta\Delta} (z(t) - \gamma) \quad (2.18)$$

The unconditional mean of $z(t + \Delta)$ in eq. (2.11) is given by:

$$E(z(t + \Delta)) = \gamma (1 - e^{-\beta\Delta}) + e^{-\beta\Delta} E(z(t)),$$

which implies, given the stationarity of the z process, i.e. $E(z(t + \Delta)) = E(z(t)) = E(z)$, that:

$$E(z) = \gamma. \quad (2.19)$$

Finally, the unconditional variance of $z(t + \Delta)$ in eq. (2.11) is given by:

$$\text{Var}(z(t + \Delta)) = e^{-2\beta\Delta} \text{Var}(z(t)) + \rho^2 e^{-2\beta\Delta} \int_t^{t+\Delta} e^{2\beta(\tau-t)} d\tau,$$

which implies, for $\text{Var}(z(t + \Delta)) = \text{Var}(z(t)) = \text{Var}(z)$, that:

$$\text{Var}(z) = \frac{\rho^2}{2\beta} \quad (2.20)$$

Expressions (2.10)-(2.20) provide a complete statistical description over any discretization interval Δ of the continuous time stock price model in (2.5)-(2.7). Next, we present some of the key results in our paper by demonstrating how the unobserved continuous time parameters are embodied in the observed regression coefficients.

2.3.2 Investment Horizon and Autocorrelation Coefficients

In Fama and French's (1988) study, a U-shaped pattern in autocorrelation coefficients over different investment horizons is expected theoretically when a temporary component exists. We show below that this is also a feature of our continuous time model in which, indeed the autocorrelation coefficient varies with the investment horizon - as in Fama and French -, but most importantly depends on the intrinsic continuous time parameters which we aim to recover.

The continuously compounded rate of return over a single holding period Δ , say from time t to $(t + \Delta)$, is $r(t, t + \Delta) = p(t + \Delta) - p(t)$, which can be written in view of eq.

(2.5) as:

$$r(t, t + \Delta) = [q(t + \Delta) - q(t)] + [z(t + \Delta) - z(t)]. \quad (2.21)$$

The correlation coefficient between $r(t, t + \Delta)$ and $r(t - \Delta, t)$ is defined as:

$$\hat{\lambda}_{\Delta} = \frac{Cov(r(t, t + \Delta), r(t - \Delta, t))}{Var(r(t - \Delta, t))}. \quad (2.22)$$

We show in Appendix 2.1 how the above covariance and variance terms can be expressed in terms of the unobserved continuous time parameters of the model (2.5)-(2.7) to obtain, after simple rearrangements, the following reduced-form expression for the estimated correlation coefficient $\hat{\lambda}_{\Delta}$:

$$\hat{\lambda}_{\Delta} = \frac{-(e^{-\beta\Delta} - 1)^2 \frac{\rho^2}{2\beta}}{-\frac{\rho^2}{\beta}(e^{-\beta\Delta} - 1) + \sigma^2\Delta}. \quad (2.23)$$

Similarly, the autocorrelation coefficient over n discrete periods is given by

$$\hat{\lambda}_{n\Delta} = \frac{-(e^{-\beta n\Delta} - 1)^2 \frac{\rho^2}{2\beta}}{-\frac{\rho^2}{\beta}(e^{-\beta n\Delta} - 1) + \sigma^2 n\Delta}, \quad (2.24)$$

Thus the correlation between returns defined over different investment horizons depends upon:

- (a) the length of the investment horizon (n), and
- (b) the properties of the stochastic process underlying stock returns, as expressed in this case by the sign and magnitude of the parameters β , ρ , and σ .

In particular, the correlation coefficient $\hat{\lambda}_{\Delta}$ for given values of the parameters of the underlying stochastic process tends to zero for very small or very large investment hori-

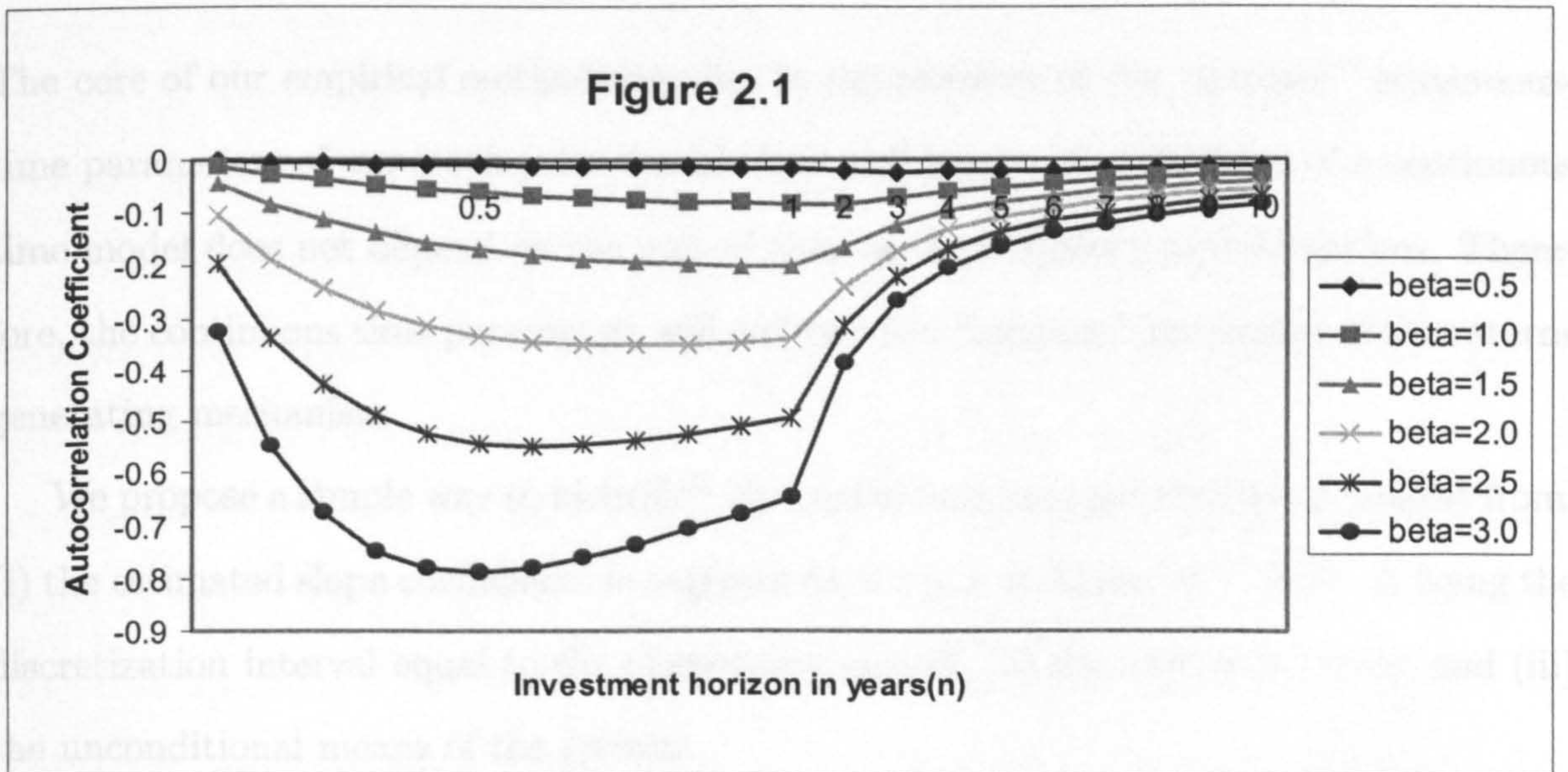
zons.

$$\lim_{n \rightarrow \infty} \hat{\lambda}_{n\Delta} = 0$$

and

$$\lim_{n \rightarrow 0} \hat{\lambda}_{n\Delta} = 0 \quad (2.25)$$

This implies that the maximum (negative) value of the autocorrelation coefficient is attained at some point in the interval $0 < n < \infty$.⁸ The value of the correlation coefficient for different values of β (beta) and over different investment horizons is evaluated using expression (2.24) and is shown in Figure 2.1. To uncover the importance of the mean reverting parameter in establishing the autocorrelation patterns of equity returns we fix the volatility parameters σ and ρ at the values of 0.15 and 0.13 respectively, which is approximately the average annualized value of each volatility coefficient across the stock markets and for the sample period covered in this study (see Tables 2.3 and 2.4).⁹



⁸Partial differentiation of $\hat{\lambda}_{\Delta}$ with respect to n yields the value of n at which $\hat{\lambda}_{\Delta}$ is minimized. In turn, linearizing around $n = 1$ yields an expression for n in terms of β and Δ only.

⁹The relative variances of the random walk and mean reverting components ($\frac{\sigma}{\rho}$) only affects the curvature of the U-shaped function.

Figure 2.1 shows that the autocorrelation coefficient between returns exhibits the U-shaped pattern of Fama and French across investment horizons. The bigger the mean-reverting parameter β , the bigger the autocorrelation coefficient is. Furthermore, for different (theoretical) values of the mean reverting parameter β (between 0.5 and 3.0), the (theoretical) half-life of mean reversion ranges from one half to three years. Note that when $\beta = 0$, $\hat{\lambda}_{n\Delta}$ is also equal to zero, which implies that if there is no “intrinsic” mean reversion in the stock price process, then the returns autocorrelation coefficient is zero irrespective of the investment horizon and the values of σ and ρ . We will evaluate next whether such a pattern in stock returns can be found empirically using the continuous time parameter estimates of the stock price model in (2.5)-(2.7) in the context of the G-7 national stock markets.

2.4 Empirical Methodology

The core of our empirical methodology lies in the recovery of the “intrinsic” continuous-time parameters of our stock price model. It is well known that the form of a continuous time model does not depend on the unit of time or the frequency of observations. Therefore, the continuous time parameters will embody the “intrinsic” properties of the returns generating mechanism.

We propose a simple way to identify¹⁰ the continuous time parameters of interest from: (i) the estimated slope coefficients in regressions of $r(t, t + \Delta)$ on $r(t - \Delta, t)$, Δ being the discretization interval equal to the observation period, (ii) the autocovariances, and (iii) the unconditional means of the returns.

We use non-overlapping data throughout our estimation procedures. Richardson and

¹⁰ Schwartz and Smith (1997) use Kalman filtering procedures to estimate the continuous time parameters. Alternatively, a Generalized Method of Moments estimation technique can be employed.

Stock (1989) point out that assessing the significance of variance ratios and autocorrelation statistics using standard asymptotic theory may provide a poor approximation to the sampling distribution, especially with overlapping data. In particular, Valkanov (2003) shows that in long-horizon regressions with overlapping data the stochastic order of the variables is altered, resulting in unorthodox limiting distributions of the slope estimator and its t-statistic.¹¹ More intuitively, Richardson (1993) argues that the Fama and French (1988) autocorrelation estimates and corresponding serial correlation patterns should be expected even if the true underlying model is a random walk. Estimation with overlapping data causes multiperiod autocorrelation estimators to have many sample autocovariances in common, picking up much of the same spurious autocorrelation at “close” horizons. If two coefficient estimates are far apart in terms of periods they refer to, then they have very little in common, and they are close to their unconditional average of zero. This may be a valid explanation for the observed by Fama and French (1988) U-shaped pattern in stock-return data, consistent with a random walk model in equity prices. Our estimation procedure obviates the need for long time series, thus allowing us to use non-overlapping data and clarify whether the regularities of equity returns documented by previous empirical studies exist, or are merely induced by overlapping data series.

The continuous time unknown parameters in equation (2.23) are: (i) the speed-of-adjustment coefficient of the temporary component β , (ii) the instantaneous variance of the temporary component ρ^2 , and (iii) the instantaneous variance of the permanent component σ^2 . It is obvious that none of these parameters is identifiable from eq. (2.23) alone. However, we can identify the speed-of-adjustment coefficient, β , by focusing on the unconditional covariance of non-overlapping returns: The numerator of (2.23) is the covariance between $r(t, t + \Delta)$ and $r(t - \Delta, t)$, the sum of expressions (A4) and (A8) in

¹¹In a rolling summation of series integrated of order zero (or $I(0)$), the new long-horizon variable behaves asymptotically as a series integrated of order one (or $I(1)$). Thus long-horizon regressions will always produce significant results.

Appendix 2.1:

$$Cov(r(t, t + \Delta), r(t - \Delta, t)) = - (e^{-\beta\Delta} - 1)^2 \frac{\rho^2}{2\beta}. \quad (2.26)$$

Similarly, choosing 2Δ to be the discretization interval:

$$Cov(r(t, t + 2\Delta), r(t - 2\Delta, t)) = - (e^{-2\beta\Delta} - 1)^2 \frac{\rho^2}{2\beta}. \quad (2.27)$$

Generally, it is straightforward to prove that for arbitrary non-overlapping discretization intervals the covariances between returns are given by the following formula:

$$Cov(r(t, t + n\Delta), r(t - n\Delta, t)) = - (e^{-\beta n\Delta} - 1)^2 \frac{\rho^2}{2\beta}, \text{ for } n = 1, 2, \dots \quad (2.28)$$

For given Δ , dividing equation (2.26) by equation (2.27) we can identify β .¹² Substituting the value of β back in (2.26) we can identify ρ^2 . In turn, using the values of β, ρ^2 , and $\hat{\lambda}_\Delta$ we can identify σ^2 from equation (2.23). Finally, the unconditional mean of $r(t, t + \Delta)$ was found in section 2.3.1 to be equal to:

$$E(r(t, t + \Delta)) = \gamma + \alpha \quad (2.29)$$

Similarly,

$$E(r(t, t + 2\Delta)) = \gamma + 2\alpha. \quad (2.30)$$

It is clear from expressions (2.29) and (2.30) that we can identify uniquely - for given Δ - the remaining continuous time parameters of interest γ (i.e. the long-run mean of the temporary component) and α (i.e. the instantaneous mean of the permanent component).

¹²Call $Cov(r(t, t + \Delta), r(t - \Delta, t)) = X$, and $Cov(r(t + 2\Delta), r(t - 2\Delta, t)) = Y$. It follows from eq.(2.26) and eq.(2.27) that $\frac{X}{Y} = \frac{(e^{-\beta} - 1)^2}{(e^{-2\beta} - 1)^2}$. In turn, $(\frac{X}{Y})^{\frac{1}{2}} = \frac{e^{-\beta} - 1}{e^{-2\beta} - 1}$. Call $z = e^{-\beta}$; then $z^2 = e^{-2\beta}$. Therefore, $(\frac{X}{Y})^{\frac{1}{2}} = \frac{z - 1}{z^2 - 1}$, which implies that $z^2\sqrt{X} - z\sqrt{Y} + (\sqrt{Y} - \sqrt{X}) = 0$, which implies that $z_{1,2} = \frac{\sqrt{Y} \pm \sqrt{Y} \mp 2\sqrt{X}}{2\sqrt{X}}$. Then, $z_1 = \sqrt{\frac{Y}{X}} - 1$, and $z_2 = 1$. Finally, since $z = e^{-\beta}$, it follows that $\beta = -\ln z_1$.

Table 2.1 collects the formulae used for identification of the continuous-time parameters.

2.5 Data and Empirical Results

2.5.1 Description of the Data

Daily data are obtained from *Datastream* for stock market indices of the G-7 countries, i.e. US, UK, Japan, France, Canada, Germany, Italy. The sample covers the period from 01/01/1982 to 01/01/2002, for a total of 5195 observations. The data used are value-weighted indices constructed by *Datastream*. Closing index prices are used which initially do not include dividends. The daily dividend yield corresponding to each stock index is also obtained and added to closing prices to generate another set of index prices including dividends.¹³

We generate continuously compounded daily returns (close-to-close) for all indices, and by summing the daily returns over 5 trading days we generate weekly returns (in the case of the United States). Since the primary objective of this paper is to nest mean reversion within the underlying continuous time stochastic process for equity indices, we use primarily “short” holding period returns - up to 1 week -, although our estimation methodology can be easily extended to “longer” investment horizons.

Table 2.2 presents summary statistics for our data set. Following the critique by Richardson and Stock (1989) and Richardson (1993) we use non-overlapping returns. As can be seen from Table 2.2 all equity indices are negatively skewed and leptokurtic. Application of standard unit root tests indicates that our equity index series can be treated as integrated of order one, $I(1)$, processes.

¹³The *Datastream* indices represent to a large extent the stock markets in the different countries and provide consistency, transparency, and international comparability. They also tend to be highly correlated with other well-known indices. For instance, the *Datastream* index for the London Stock Exchange has a correlation coefficient with the FTSE ALL SHARE of 0.99 over our sample period.

2.5.2 Empirical Results

Section 2.4 demonstrates that we can test for mean reversion by identifying the continuous-time parameters of the stochastic stock price model (2.5)-(2.7) using equations (2.26)-(2.30). Using the Ordinary Least Squares (OLS) estimation procedure, we first estimate slope coefficients in regressions of $r(t, t + \Delta)$ on $r(t - \Delta, t)$ for discretization intervals $\Delta = 1$ day for all the countries in our sample except for the US (where we use $\Delta = 1$ week, see page 57). Throughout we use non-overlapping data on continuously compounded returns to avoid inducing spurious correlation and serious biases in our continuous-time coefficient estimates. It should be noted that in contrast to Fama and French (1988) and the other empirical literature, we do not assess the overall performance of our mean reverting stock price model by evaluating the return correlation coefficient across different investment horizons. Rather, the important point in our testing methodology is to extract the continuous time parameters from the estimated discrete time equations, notably, the speed-of-adjustment coefficient of the temporary component β which induces “intrinsic” mean reversion in the stock price process. Initial estimation of the autocorrelation coefficients for the discretization intervals mentioned above serves merely the purpose of recovering the volatility parameter σ and the standard errors of the continuous-time parameters.

The statistical significance of the continuous time parameters was evaluated by invoking large sample theory and using a simple application of the log-linearization process known as the delta method (see Appendix 2.2). The unknown parameters were expressed as functions of the estimated autoregressive coefficients $\hat{\lambda}_\Delta$ - in particular, the autocovariances of returns which appear in the identifying formulas for β, ρ , and σ were formulated as the product of the estimated autocorrelation coefficients and return variances -, and the standard errors obtained as log-linear functions of the standard errors of $\hat{\lambda}_\Delta$. Asymptotic normality is assumed throughout and standard errors are corrected for the heteroskedas-

ticity observed in returns using White's correction (1980).

Tables 2.3 and 2.4 show the estimated continuous time parameters for the seven national stock market indices. Table 2.3 ignores dividends while Table 2.4 presents results inclusive of dividends sampled at the daily frequency. It is well known that by ignoring dividends a spurious pattern of mean reversion may be generated, especially at the higher frequencies. If dividends are paid out but ignored in the data, we may expect a sudden negative return at the time that dividends are paid. Over time this negative return will be reversed as the payment date for the next dividend comes nearer and becomes incorporated in prices. The positive, statistically significant point estimate of the all-important speed-of-adjustment coefficient β , both with and without dividends, demonstrates strong evidence for mean reversion even at the daily frequency for five countries (Canada, France, Germany, Italy, UK) and at the weekly frequency for the US. We had to change the discretization period for the US since convergence in our numerical and statistical estimation procedures could not be achieved for daily data. In particular, values for the dividend inclusive β are smaller in magnitude (except for the UK and France, where they are marginally higher) than corresponding estimates from Table 2.3, as expected, but only marginally so. In the case of Japan, a negative, but insignificant, β is obtained both with and without dividends.¹⁴

Naturally, given the maintained hypothesis of mean reversion at all horizons according to the model of equations (2.5)-(2.7), it is appropriate to infer correlations at long horizons from correlations at short horizons, as in figure 2.1. It is true, however, that our findings may be attributed to spurious mean reversion caused by the bid-ask bounce, especially when one uses - as we do - daily observations. Our indices for the G7 economies are constructed from the last recorded trade of each day and one cannot assess whether it

¹⁴Given the historical performance of the Japanese equity markets during the sample, with the prolonged boom period in the 1980s, and the bust period of the 1990s, it does not come as a surprise that we report a negative and insignificant value for the mean reverting coefficient. Also Table 2.5 shows that effectively no temporary component exists in Japanese stock prices (around 1% of the variation in returns is accounted for by the stationary component).

is a bid or ask price. We acknowledge that closing prices, as compared, for example, to midpoints of bid-ask prices may cast doubt on the intrinsic nature of our mean reverting results. We have experimented, though, with index data for the UK alone for which the bid-ask price was available and still found evidence of statistically significant mean reversion: Bid-ask closing prices are available for the UK Datastream index until October 1997. Bid-to-bid closing returns produce a β of 1.8654, ask-to-ask closing returns a β of 1.8521, and the midpoint of bid-ask closing returns a β of 1.8501, all statistically significant. Furthermore, since the indices are value-weighted, the effect of infrequent or non-synchronous trading (e.g. Lo and Mackinlay (1990b), Lehmann (1990)) on our results, which is concentrated in small stocks, is mitigated. What's more to the purpose, such effects have been shown to induce positive serial correlation in stock portfolios (e.g. Lo and Mackinlay (1990b), Bessembinder and Hertz (1993)), and if anything, should bias our results against mean reversion. Finally, we have also investigated the effect of "dead stocks" dropping out of the index, by using value-weighted recalculated index data which only account for the historical performance of the index constituents as at 01/01/2002 over the sample period. Results are quite similar to Tables 2.3 and 2.4 and are not reported to conserve space.

The results suggest a half-life of mean reversion for all markets involved of between one-half and two years (the minimum of the curves, see figure 2.1). Note that markets seem to react faster to temporary shocks than other studies have suggested. For example, Balvers et al (2000) in their multi-country study report a speed of mean-reversion with a half-life of three to three and one-half years. However, we use more recent data at higher frequencies than previous studies to find that the speed of mean reversion towards the specified stochastic trend path of stock prices has risen, which implies lower degree of persistence in the temporary component of stock prices. It seems that stock markets are becoming more efficient over time, reaping the benefits of globalization.

2.5.3 Dynamic Simulations

Dynamic simulations for equity returns are carried out in order to evaluate our theoretical mean-reverting model using the estimated continuous time parameters for all countries. To start the simulations, we need an initial value for the temporary component, $z(t)$. Following Poterba and Summers (1988), this is estimated as the share of return variation over the sample period due to the transitory component (see Table 2.5) multiplied by the initial sample price. 1,000 replications of model (2.5)-(2.7) are carried out and the Mean-Squared-Error (MSE) was calculated by comparing the average return path from the simulations to the actual returns of the seven stock market indices. For all markets, the low MSE values indicate that the proposed theoretical model is consistent with the empirical behavior of stock returns.

2.6 Conclusion

In this chapter we develop a continuous time stock price model with the intention to study stock returns predictability and reappraise the voluminous empirical literature. Mean reversion in stock returns is better examined within a continuous time framework since most of the conflicting results in the literature arise from the specification of the “holding time period” in stocks, a notion which becomes at least theoretically irrelevant in a continuous time setting. Our theoretical framework nests with the modeling philosophies of earlier studies and assumes that stock returns are generated by the joint effect of a stationary component, modelled as an Ornstein-Uhlenbeck process, and a nonstationary component, modelled by an Arithmetic Brownian motion process. The general hypothesis in our model is that stock prices are nonstationary processes in which the permanent gain from each period’s shock is less than 1.0; the temporary shock will be gradually eliminated.

Using conventional return autocorrelation tests, we develop reduced form expressions

of the slope coefficient that embodies the continuous time parameters without relying on crude approximations of the continuous time stochastic processes that typically lead to temporal aggregation biases. In turn, we develop a methodology for the identification of the continuous-time parameters of interest from unconditional covariances over non-overlapping intervals, slope coefficients, and unconditional means of stock returns. Finally, we use the identified parameters to examine how they cause the autocorrelation coefficient between stock returns to vary with the investment horizon. Not surprisingly, we are able to confirm that the famous U-shaped pattern in returns autocorrelations is an empirical phenomenon.

For the first time in the literature we report statistically significant evidence of mean reversion in daily data for Canada, France, Germany, Italy, and the UK, and also find evidence of mean reversion in weekly data for the US (in agreement with Lehmann (1990)). Dynamic simulation experiments suggest that our theoretical model is consistent with the empirical behavior of stock returns.

An obvious extension of our work is to utilize Lo and Wang's (1995) framework for pricing index options in a mean reverting framework. This is easily accomplished since we estimate the continuous time volatility parameters.

Up to now, the common wisdom in the literature was that mean reversion, if it exists, is thought to be slow and can only be picked up over long horizons. We believe that our paper contributes to the finance literature through our findings in the context of seven national stock markets. To paraphrase Campbell et al. (1997), we "can tell" that mean reversion exists in stock prices.

Table 2.1
Formulae for the Recovery of the Continuous Time Parameters

Parameter	Description	Identifying Formula
β	adjustment speed of temporary component	$-\ln \left\{ \left[\frac{Cov(r(t, t+2\Delta), r(t-2\Delta, t))}{Cov(r(t, t+\Delta), r(t-\Delta, t))} \right]^{\frac{1}{2}} - 1 \right\}$
ρ	instantaneous stdev of temporary component	$\left\{ \left[\frac{2\beta Cov(r(t, t+\Delta), r(t-\Delta, t))}{(e^{-\beta\Delta} - 1)^2} \right]^{\frac{1}{2}} \right\}$
σ	instantaneous stdev of permanent component	$\left\{ \frac{Cov(r(t, t+\Delta), r(t-\Delta, t))}{\hat{\lambda}_\Delta} + \frac{\rho^2}{\beta} (e^{-\beta\Delta} - 1) \right\}^{\frac{1}{2}}$
α	instantaneous mean of permanent component	$E(r(t, t+2\Delta)) - E(r(t, t+\Delta))$
γ	long-run mean of temporary component	$E(r(t, t+\Delta)) - \alpha$

Note: The continuous time parameters of the model (2.5)-(2.7) are reported together with their descriptions and the formulae used for their identification and recovery

Table 2.2
Summary Statistics

	Mean	Min	Max	Stdev.	Skew.	Kurt.	ADF
CANADA	0.0004	-0.1165	0.0876	0.0079	-1.1824	22.274	-45.68 ^a
FRANCE	0.0007	-0.0986	0.0806	0.0111	-0.5431	6.1185	-61.62 ^a
GERMANY	0.0005	-0.1264	0.0670	0.0118	-0.6840	7.9162	-65.00 ^a
ITALY	0.0005	-0.0843	0.0840	0.0127	-0.2054	3.8559	-60.44 ^a
JAPAN	0.0001	-0.1614	0.1243	0.0128	-0.1933	10.862	-60.51 ^a
UK	0.0005	-0.1301	0.0649	0.0088	-1.1416	16.099	-59.78 ^a
US	0.0028	-0.3049	0.1158	0.0242	-2.3588	28.942	-49.73 ^a

Note: Summary statistics are reported for non-overlapping continuously compounded returns for all equity indices included in our sample. Daily data are used for all countries from 01/01/1982 to 01/01/2002, except for the US where weekly returns are employed. The ADF statistic in the last column refers to the Augmented Dickey Fuller statistic which tests for stationarity of equity index returns. ^a indicates rejection of the null hypothesis of non-stationarity at the 1% significance level.

Table 2.3

Continuous Time Parameters (Dividend Exclusive)

	β	ρ	σ	α	γ
CANADA	2.2319 ^a	0.0074 ^a	0.0064 ^a	0.0003	0.0000
FRANCE	2.6839 ^b	0.0082 ^c	0.0093 ^a	0.0007	0.0000
GERMANY	1.9308 ^b	0.0052 ^c	0.0113 ^a	0.0005	0.0000
ITALY	3.7051 ^a	0.0116	0.0114 ^a	0.0004	0.0000
JAPAN	-0.8432	0.0009	0.0128 ^a	0.0002	0.0000
UK	2.0539 ^a	0.0063 ^a	0.0078 ^a	0.0003	0.0000
US	1.5325 ^a	0.0171	0.0217 ^a	0.0028	0.0000

Note: The continuous-time parameters for the seven national stock indices when index returns do not include dividends are reported. Standard errors were calculated using the Delta Method and are adjusted for heteroskedasticity. ^a, ^b, and ^c denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.4

Continuous-Time Parameters (Dividend Inclusive)

	β	ρ	σ	α	γ
CANADA	2.1964 ^a	0.0072 ^a	0.0062 ^a	0.0003	0.0000
FRANCE	2.7021 ^a	0.0080 ^c	0.0110 ^a	0.0007	0.0000
GERMANY	1.8608 ^b	0.0051 ^c	0.0111 ^a	0.0005	0.0000
ITALY	3.6010 ^a	0.0112	0.0110 ^a	0.0004	0.0000
JAPAN	-0.7627	0.0011	0.0127 ^a	0.0002	0.0000
UK	2.1600 ^a	0.0061 ^a	0.0075 ^a	0.0003	0.0000
US	1.4927 ^a	0.0169	0.0219 ^a	0.0028	0.0000

Note: The continuous-time parameters for the seven national stock indices when index returns include dividends are reported. Standard errors were calculated using the Delta Method and are adjusted for heteroskedasticity. ^a, ^b, and ^c denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.5
Dynamic Simulations

	%of return variation due to stationary component	Mean Squared Error
CANADA	34.8	0.0018
FRANCE	21.3	0.0012
GERMANY	8.57	0.0012
ITALY	21.4	0.0014
JAPAN	1.00	0.0015
UK	21.7	0.0010
US	24.3	0.0008

Note: Dynamic Simulation Results for the seven national stock indices are reported above. The percentage of return variation attributable to the stationary component for the relevant countries is reported, as well as the mean squared error when actual returns are compared with returns simulated using the model (2.5)-(2.7). Since $r(t, t + \Delta) = [q(t + \Delta) - q(t)] + [z(t + \Delta) - z(t)]$ (see expression (2.21)), then $Var[r(t, t + \Delta)] = Var[q(t + \Delta) - q(t)] + Var[z(t + \Delta) - z(t)] = \sigma^2 \Delta - \frac{\rho^2}{\beta} (e^{-\beta \Delta} - 1)$ from expressions (A9) and (A5) respectively in Appendix 2.1. Therefore, the share of return variation due to the stationary component is equal to

$$1 - \frac{\sigma^2 \Delta}{\sigma^2 \Delta - \frac{\rho^2}{\beta} (e^{-\beta \Delta} - 1)}$$

Chapter 3: On the Returns Generating Process and the Profitability of Trading Rules in Emerging Capital Markets

3.1 Introduction

In recent years, emerging capital markets (henceforth ECM) have attracted a great deal of attention from investors and investment funds seeking to diversify their portfolios. Notwithstanding their high risk, the higher sample average returns and low correlations with developed market returns are two of the distinguishing features of ECM returns (Bekaert and Harvey (1997)) that have made such markets increasingly attractive to international investors.¹ Such characteristics, coupled with the financial liberalization process these countries have embarked on, have led to a dramatic increase in capital flows since the early 1990s, with portfolio flows (fixed income and equity) and foreign direct investment replacing commercial bank debt as the dominant sources of foreign capital (Bekaert and Harvey (2003)).²

Despite the significance of ECM as important conduits of international diversification, little has been said in the literature about the statistical returns generating process, and the profitability of trading rules in these markets. The principal aim of this Chapter is to fill this void in the literature by modeling the dynamic behavior of stock returns in ECM and assessing the potential profitability of popular trading strategies.

Recent studies show that emerging markets tend to exhibit higher volatility (both

¹For the diversification benefits of emerging market investments see, among others, De Santis (1993), Harvey (1995a), Bekaert and Urias (1996, 1999), De Roon et al. (2001), and Li et al. (2003). The message from these studies is that the diversification benefits of holding emerging market indices (as measured by the International Finance Corporation (IFC)), or open-end funds which track the IFC indices very well, remain substantial even when transaction costs and short-sale constraints are taken into account.

²For example, using data from 16 emerging markets, Bekaert and Harvey (2003) show that the U.S. share of market capitalization has almost doubled in the 1990s compared with the 1980s, whereas in dollar terms, U.S. holdings have increased 10-fold in the 5-years post-liberalization versus the 5-years pre-liberalization.

conditional and unconditional) compared with developed markets (see, for example, De Santis and Imrohoroglu (1997), Bekaert and Harvey (1997)), as well as higher persistence in stock returns. Bekaert (1995), Bekaert and Harvey (1995), and Harvey (1995a,b) report statistically significant sample autocorrelations in emerging market returns. Such evidence could be attributed to some form of market inefficiency offering opportunities for excess returns, even after adjusting for risk. It could also reflect a more persistent variation of risk factors in ECM. As noted by Wright (1999), persistence in equity returns of ECM could potentially reflect a lack of liquidity, though Harvey (1995b) argues against this possibility.³

Persistence in equity returns may be attributed to long range dependence, or long memory, in the returns time series. Arguably, ECM are more likely to exhibit such characteristics than developed markets. Market thinness and nonsynchronous trading biases should be expected to be more severe in ECM, given their low level of liquidity (De Santis and Imrohoroglu (1997)). Also, “learning effects” are bound to be important since investors in ECM tend to react slowly and gradually to new information (Barkoulas et al. (2000)). In addition, the mounting evidence of nonnormality and nonlinearities in ECM returns (see, for example, Harvey (1995a), Bekaert and Harvey (1997)), is consistent with a persistent (either in mean and/or volatility) return generating process in emerging markets.

Such characteristics of a market suggest that technical trading rules could be profitable.⁴ Technical trading analysis assumes that the patterns in past security price series

³Urrutia (1995) is skeptical about the interpretation of autocorrelation in emerging markets, and offers another explanation: Since both the economy and the capital markets of developing economies are growing at unusually fast rates, it is possible that autocorrelations are indicators of economic growth rather than evidence against the efficient market hypothesis.

⁴Van Der Hart et al. (2003) examine the profitability of a broad range of stock selection strategies by studying 3000 securities in 32 emerging markets over the period 1985-1999. They find that value and momentum strategies generate significant excess returns, in contrast to strategies based on size and mean reversion, even after accounting for low liquidity, outliers in stock returns, an implementation delay, and transaction costs faced by large institutional investors. They confirm that the profitability of such strategies cannot be explained by traditional asset pricing models. Moreover, they do not find a pronounced effect of financial market liberalization on the performance of the strategies.

will recur in the future, and can thus be used for predictive purposes. Furthermore, technical analysis may be used to uncover hidden patterns in stock returns not picked up by standard statistical tests, which can help to better forecast prices.⁵

Although such investigations and issues have been partly dealt with in the case of developed markets (see, for example, Brock et al. (1992) and Bessembiner and Chan (1998) for the US, Hudson et al. (1996) for the UK), there has been, to the best of our knowledge, no extensive study of this sort regarding ECM. Two questions are being predominantly addressed in this Chapter: First, the existence of long memory in the mean and variance of ECM stock return dynamics. Second, the relative profitability over and above the buy and hold strategy of popular trading rules such as Moving Average and Trading Range Break strategies. The impact of transaction costs and measurement errors in returns is also examined. Furthermore, by employing the “double-or-out” scheme we investigate whether excess - to the buy and hold - returns generated by our trading rules come at the expense of unduly higher risk.

Since the influential paper of Sullivan et al. (1999), any apparent success of trading rules has been confronted with an appropriate degree of scepticism due to data snooping biases. In order to reduce the possibility of reporting spurious results, in the empirical part of the chapter we are employing a previously unexplored data set; it is well known that data snooping is aggravated by repeated investigations of the same data set. We are using the Morgan Stanley Capital International (MSCI) daily stock index price series for eight emerging markets which fall into two geographical regions: Latin America (Argentina, Brazil, Chile, Mexico) and Asia (Indonesia, Philippines, Taiwan, Thailand). A mix of different exchanges is included in our sample and the stock markets examined vary in age, size, and spread of securities traded. Moreover, we are interested in comparing results across regions, given that Latin American markets have been more “open” during

⁵ Predictability of returns over short horizons can also be due to market microstructure effects. Reversals in recorded returns can be accounted for by movements from the bid to the ask. Since our trading strategies are not based on return reversals, this microstructure explanation is implausible.

the late 1980s and 1990s compared to their Asian counterparts.

Our methodology follows the studies by Brock et al. (1992), Levich and Thomas (1993), Osler and Chang (1995) and Sullivan et al. (1999), as standard statistical tests are augmented by the bootstrap methodology to carry out statistical inferences on trading rule profitability and ability to forecast future price changes. However, our study differs in that we decide on the particular specification of the double long memory ARFIMA-FIGARCH model that is empirically supported in each market. We conduct bootstrap simulations of the underlying returns process using the estimated parameters and standardized residuals for the fitted model and apply our trading rules on each of the simulated series. The ability of the econometric model to generate trading rule results consistent with actual data is examined.

The remainder of this chapter is organized as follows. In Section 3.2 we analyze the theoretical foundations of parametric long memory models and assess the empirical evidence. We also review the academic literature on technical trading rule predictability/profitability in stock markets and discuss the major empirical findings. In Section 3.3 we present the econometric framework employed in modeling ECM returns dynamics and its rationale. Section 3.4 addresses the trading strategy methodology and the bootstrap procedure. Section 3.5 presents the data set. Section 3.6 analyses our empirical results and assesses their significance. Finally, Section 3.7 concludes the chapter.

3.2 Literature Review

3.2.1 Parametric Long Memory Models

The dynamic behavior of stock prices and their conditional volatility has been the focus of many empirical studies in the financial literature. Characterizing the returns generating mechanism is a crucial issue for asset and risk management, asset pricing and portfolio al-

location. Conditional second moments play a key role in portfolio diversification and risk hedging strategies, which rely on the ability to predict variances and covariances. Volatility is also an input in derivative pricing models. As De Santis and Imrohoroglus (1997) note, although most emerging markets still lack sophisticated financial instruments, characterizing the distribution and dynamics of stock prices is a first necessary step towards their development.

The presence of long memory in asset prices allows returns to exhibit significant autocorrelation between distant observations. This contradicts the weak form of the Efficient Market Hypothesis. If the series realizations are not independent over time, then past returns can be used to forecast future returns, giving rise to consistent speculative profits. Also, optimal consumption/savings and portfolio decisions may become sensitive to the investment horizon if stock returns were long-range dependent. If financial time series exhibit long memory, then their unconditional probability distributions may not be normal. This has important implications for many areas in finance, especially asset and option pricing, portfolio allocation and risk management. Moreover, Mandelbrot (1971) observes that in the presence of long memory the arrival of new market information is not fully arbitrated away and martingale models of asset prices cannot be obtained from arbitrage. Thus pricing derivative securities with martingale methods may be inappropriate if the underlying stochastic process exhibits long memory.

There are several possible definitions of the property of long memory.⁶ From an empirical, data-orientated approach, the presence of long memory may be defined in terms of the persistence of observed autocorrelations (strong dependence between distant observations). The extent of the persistence is consistent with an essentially stationary process, but the autocorrelations take far longer to decay than the exponential rate associated with the stationary ARMA class of processes. A long memory process can thus be re-

⁶The long memory property might be defined also in terms of the spectral density (see Beran (1994)). An alternative definition of long memory is in terms of Wold decomposition. For a survey see Baillie (1996).

garded as a halfway house between the restrictive $I(0)$ and $I(1)$ paradigms. Defining the autocorrelation between observation at time t and observation at time $t - j$ as ρ_j , long memory processes are characterized by the following property:

$$\lim_{t \rightarrow \infty} \sum_{j=-t}^t |\rho_j| = \infty \quad (3.1)$$

Fractionally integrated processes are long memory processes given the definition in (3.1). In particular, the process y_t is said to be integrated of order d , or $I(d)$, if

$$(1 - L)^d y_t = u_t \quad (3.2)$$

where L is the lag operator, $-0.5 < d < 0.5$, and u_t is a stationary and ergodic process. When $d = 0$, $y_t = u_t$, so “weakly autocorrelated” y_t is allowed for. When $d = 1$, y_t has a unit root. For $0 < d < 0.5$, the process is long memory in the sense of condition (3.1), and its autocorrelations are all positive and exhibit a hyperbolic rate of decay – the process, however, is still stationary -. Therefore, the exponent d tames down the unit root and introduces the long memory. For $-0.5 < d < 0$, the sum of absolute values of the autocorrelations of the process tends to a constant, so that it has short memory according to (3.1). Thus fractionally integrated processes are intermediate between $I(0)$ and $I(1)$ processes.

Following Granger and Joyeux (1980) and Hosking (1981), we may rewrite (3.2) as follows:

$$(1 - L)^d (y_t - \mu) = u_t \quad (3.3)$$

where μ is the unconditional mean of the process y_t , $E(u_t) = 0$, $E(u_t^2) = \sigma^2$, and $E(u_t u_s) = 0$ for $s \neq t$. Equation (3.3) defines a fractional white noise process. The

fractional difference operator $(1 - L)^d$ is defined as

$$\begin{aligned} (1 - L)^d &= 1 - dL + d(d-1)L^2/2! - d(d-1)(d-2)L^3/3! + \dots \\ &= \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(k+1)\Gamma(-d)} \end{aligned} \quad (3.4)$$

where $\Gamma(\cdot)$ is the standard gamma function. The asymptotic approximation of the autocorrelation function of expression (3.3) at lag j is given by

$$\rho_j \approx c j^{2d-1}$$

where

$$c = \frac{\Gamma(1-d)}{\Gamma(d)} \quad (3.5)$$

Hence for large j and $0 < d < 0.5$, the autocorrelation coefficients of process y_t exhibit slow hyperbolic decay.

Since many economic time series exhibit an autocorrelation structure which appears nonstationary, while the difference series appears over-differenced, Granger and Joyeux (1980) and Hosking (1981) separately formulated the fractionally integrated ARMA, or ARFIMA(p, d, q) process:

$$\rho(L)(1 - L)^d(y_t - \mu) = \theta(L)u_t \quad (3.6)$$

where d is the fractional differencing parameter, $\rho(L) = 1 - \sum_{j=1}^p \rho_j L^j$, $\theta(L) = 1 - \sum_{j=1}^q \theta_j L^j$, μ is the mean of the process y_t , u_t is white noise, and all the roots of $\rho(L)$ and $\theta(L)$ lie outside the unit circle. The ARFIMA class of models is very flexible and captures both short and long memory components of a process. In fact, the parameter d accounts for the long memory component, while the $\rho(L)$ and $\theta(L)$ polynomials capture the short run dynamics.

Granger and Joyeux (1980) and Hosking (1981) showed that the autocorrelation coefficients of an ARFIMA model exhibit a slow hyperbolic rate of decay. For any process $y_t \sim I(d)$, where $d < 1$, the process is mean reverting. For $-0.5 < d < 0.5$, the process is covariance stationary; if $-0.5 < d < 0$, the process is said to be “anti-persistent”, i.e. exhibits short memory, while the process exhibits long memory for $0 < d < 0.5$. While y_t will not be covariance stationary for $0.5 < d < 1$, it will nevertheless still be mean reverting. It is evident from expression (3.6) that the ARFIMA(p, d, q) specification reduces to a stable ARMA(p, q) process when $d = 0$, and an ARIMA($p, 1, q$) model for $d = 1$.

The same issues that arise in modeling long run dependencies in the first moment of a process also become relevant when the second moment is considered. The GARCH class of models (Bollerslev (1986)) has been widely used in empirical research (especially the GARCH(1, 1)) since they capture some of the main characteristics in observed data, namely volatility clustering and mean reversion in the volatility. We may define the GARCH(p, q) process, $\{\varepsilon_t\}$, as follows:

$$\begin{aligned}\varepsilon_t &= \sigma_t e_t, \quad e_t \sim i.i.d.(0, 1) \\ \sigma_t^2 &= \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2\end{aligned}\tag{3.7}$$

where, by definition, the process $\{\varepsilon_t\}$ is serially uncorrelated with mean zero, but the conditional variance of the process, σ_t^2 , is changing over time. L denotes the lag or backshift operator, ω is the constant in volatility parameter, $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \dots + \alpha_q L^q$ and $\beta(L) = \beta_1 L + \beta_2 L^2 + \dots + \beta_p L^p$. Stability and covariance stationary of the $\{\varepsilon_t\}$ process requires that $[1 - \alpha(L) - \beta(L)]$ and $[1 - \beta(L)]$ lie outside the unit circle. This stationarity condition implies that the effect of the past squared innovations on the current conditional variance decays exponentially (thus fast) with the lag length. Bollerslev (1988) showed that the squared residuals autocorrelation function in a GARCH (1, 1) decreases exponentially, and as such, the sum of the absolute values of autocorrelations converges

whereas in order to exhibit long memory the same sum should diverge. Ding and Granger (1996) extended these results for the general GARCH(p, q) case. Defining the innovations in the conditional variance process as $v_t = \varepsilon_t^2 - \sigma_t^2$, the GARCH(p, q) model in (3.7) might be expressed as an ARMA(m, p) process in ε_t^2

$$\phi(L)\varepsilon_t^2 = \omega + [1 - \beta(L)]v_t \quad (3.8)$$

where $m = \max(p, q)$ and $\phi(L) = [1 - \alpha(L) - \beta(L)]$. If the autoregressive lag polynomial in expression (3.8) contains a unit root, the GARCH(p, q) process is defined in Engle and Bollerslev (1986) to be integrated in variance – the integrated GARCH(p, q), or IGARCH(p, q) model:

$$\phi(L)(1 - L)\varepsilon_t^2 = \omega + [1 - \beta(L)]v_t \quad (3.9)$$

The IGARCH process is not weakly stationary, yet, as shown by Nelson (1990) for the IGARCH(1, 1) model and extended to the general IGARCH(p, q) case by Bougerol and Picard(1992), IGARCH models are strictly stationary and ergodic. Considerable care should thus be taken in interpreting persistence in conditional variance. From a forecasting perspective, shocks to the (future expected) conditional variance of the IGARCH model persist indefinitely, implying that pricing of risky securities (long-term options and futures) may show extreme dependence on initial conditions, contrary to observed pricing behavior. However, Ding and Granger (1996) show that the effect of a shock on the “true” (i.e. actual, not forecasted) conditional variance process is not permanent, and in fact the autocorrelation function for ε_t^2 is still exponentially decreasing, like standard stable GARCH models.

Baillie et al. (1996) introduced long memory in the conditional variance of a GARCH model and proposed the FIGARCH(p, δ, q) model, which imposes an ARFIMA structure

on ε_t^2 :⁷

$$\phi(L)(1-L)^\delta \varepsilon_t^2 = \omega + [1 - \beta(L)]v_t \quad (3.10)$$

where for $0 < \delta < 1$, δ captures the long memory effect and provides important information regarding the speed with which shocks to the volatility process are propagated, while the polynomials $\beta(L)$ and $\phi(L)$ describe the short-run effects. The FIGARCH model nests the GARCH and IGARCH specifications; when $\delta = 0$, the FIGARCH model in (3.10) reduces to a GARCH model and when $\delta = 1$ it reduces to an IGARCH model. Rearranging equation (3.10) an alternative representation for the FIGARCH(p, d, q) model is

$$[1 - \beta(L)]\sigma_t^2 = \omega + [1 - \beta(L) - \phi(L)(1-L)^\delta]\varepsilon_t^2 \quad (3.11)$$

Thus, the conditional variance of ε_t is simply given by

$$\sigma_t^2 = \omega[1 - \beta(1)]^{-1} + \lambda(L)\varepsilon_t^2$$

where

$$\lambda(L) = 1 - \frac{(1 - \phi(L))(1-L)^\delta}{1 - \beta(L)} \quad (3.12)$$

The FIGARCH model in (3.11) implies a hyperbolic rate of decay for the lagged squared innovations, which is a characteristic of long memory processes. Baillie et al. (1996) point out that the second moment of the unconditional distribution of $\{\varepsilon_t^2\}$ is infinite, and thus the FIGARCH process is not weakly stationary; however, the FIGARCH(p, δ, q) class of

⁷Independent research by Ding and Granger (1996) leads to a closely related model. Bollerslev and Mikkelsen (1996) extended the FIGARCH specification to a log transformation of the conditional variance process and proposed the Fractionally Integrated Exponential GARCH (see Nelson (1991)). This model, however, implies long memory features for the logarithm of squared returns, and since the discussion in the literature is usually in terms of the levels of squared returns, we choose to work with the FIGARCH model which admits a more natural interpretation in terms of squared returns. In addition, the long memory stochastic volatility model was introduced by Breidt et al. (1998). The much easier inferential procedures for ARCH-type models is one obvious advantage of the FIGARCH approach over stochastic volatility models.

processes is strictly stationary and ergodic for $0 \leq \delta \leq 1$.

Several semi-parametric procedures also exist to test for long memory in asset returns. The most prominent examples are the modified rescaled range (R/S) statistic of Lo (1991), which renders the original R/S statistic of Hurst (1951) robust to short-term dependence, and the Geweke and Porter-Hudak (1983) spectral regression method which is, however, not robust to short-run dynamics. Moreover, through extensive Monte Carlo simulations, Cheung (1993) and Agiakoglou et al. (1993) found the spectral regression test to be biased towards findings of long memory in the presence of large autoregressive parameters and infrequent shifts in the mean. In general, we do not employ semi-parametric estimation procedures as they are not suited for joint estimation of short- and long-memory components. Moreover, “Despite the amount of theoretical work in attempting to derive robust semi-parametric estimators of long memory parameters, there is substantial evidence documenting their poor performance in terms of bias and mean squared error.” Baillie (1996, p.35).

3.2.2 Empirical Evidence of Long Memory

Many authors have tested for long memory in asset returns, including both stock and exchange rate returns. The general consensus is that stock market returns contain little serial correlation. For example, Lo (1991) finds no evidence of long memory in U.S. stock returns (equal-weighted and value-weighted CSRP indexes) using the modified R/S method. Cheung and Lai (1995) find no evidence of persistence in several international stock returns series using both the modified R/S method and the spectral regression method of Geweke and Porter-Hudak (1983). Crato (1994) reports similar evidence for the stock returns series of the G-7 countries using exact maximum likelihood estimation. Lobato and Savin (1998) use a semiparametric procedure to find no evidence of long memory in the level of the returns of the S&P 500 index (between July 1962 and December

1994) and in the returns of the stocks comprising the Dow Jones Industrial Average. Jacobsen (1996) tested for long memory in U.S., Japanese, and Western European stock index returns, Hiemstra and Jones (1997) considered long memory in U.S. individual stock returns, whereas Cheung (1993) tested for long memory in exchange rate returns, all with little evidence of long memory.

Two interesting exceptions are the studies by Barkoulas et al. (2000) and Wright (1999), which focus on emerging stock markets. The former authors report some evidence for long memory in the Greek Stock market using the Geweke and Porter-Hudak (1983) spectral regression method. Applying the same log- periodogram regression methodology to a wide range of emerging stock market returns, Wright (1999) finds some evidence for positive long memory in seven out of the seventeen series considered.

Despite the scant evidence in favor of long term persistence in asset returns, there is a lot of evidence that conditional volatility of asset returns displays long memory features. The first contribution in this regard was Taylor (1986), who noticed an apparent stylized fact that the absolute values of stock returns tended to have very slowly decaying positive autocorrelations. Ding et al. (1993), Granger and Ding (1995), and Ding and Granger (1996) also found evidence that the power transformation of absolute returns, $|r_t|^\alpha$, where α is a positive number, has high autocorrelation for long lags and that this property is strongest when $\alpha = 1$.⁸ Granger and Ding (1995) showed that the expected absolute return, and any power transformation of this return, may be interpreted as a measure of risk. Additional evidence for long memory in stock market volatility is provided, among others, by Crato and De Lima (1994), Dacorogna et al. (1993), Bollerslev and Mikkelsen

⁸Ding et al.(1993) found that $|r_t|$, where $|r_t|$ is the daily S&P500 stock market absolute returns series from 1928 to 1992, has significant positive autocorrelations at over 2,700 lags with a total of 17,054 observations. Similar results are also found for other values of α in $|r_t|^\alpha$. Ding and Granger (1996) also examine these properties for other long returns series, including the Japanese stock market index Nikkei, foreign exchange returns of the Deutchmark with the US dollar, individual stock returns for company Chevron, and minute-by-minute stock returns for a Japanese company. The only significant difference in the results for these series compared with the Ding et al. (1993) S&P 500 results is that for foreign exchange rate returns the long memory property is strongest when $\alpha = 1/4$.

(1996), and Lobato and Savin (1998).

Lobato and Savin (1998), however, were among the first to point out that findings of long memory either in the mean or volatility of asset returns could be spurious, as a result of nonstationarity (structural breaks) and aggregation in the time series considered.⁹ Nonstationarity, for example, is a plausible explanation for the findings of Ding et al. (1993), who use S&P500 data from 1928 to 1992. During this long period, there were changes in the mean of squared returns. It was very high in the early thirties, then much reduced by the end of the decade. The mid seventies and the eighties saw a substantial increase in the mean of squared returns, probably due to the introduction of new financial products and computer trading programs (see, for example, Grossman and Zhou (1996)), whereas instead there was a decrease in the nineties. However, Lobato and Savin, splitting their sample of S&P500 data into two arguably stationary periods (though their sample only covers the period from July 1962 to December 1994), find strong evidence of long memory in both periods. Granger and Ding (1995) and Granger (1998), for example, showed that although nonstationarity may affect the long memory parameter, it is still unclear if the nonstationarity results in a long memory process. More recently, Granger and Terasvirta (1999), Granger and Hyung (1999) and Diebold and Inoue (2001) suggest some cases where structural breaks are closely related with long memory. In particular, Granger and Hyung (1999) found evidence of a time-varying long memory parameter in S&P500 absolute returns, and suggest that a linear model with occasional breaks is appropriate for stock returns. Nevertheless, to the best of our knowledge, there exists no formal test yet for long memory in the presence of structural breaks when returns are not Gaussian.

Contrary to the Granger and Hyung (1999) evidence, Baillie (1998) finds little evidence of significantly time-varying long memory in long time series of the S&P500 index (thus

⁹ Earlier, Lamoureux and Lastrapes (1990) indicated that persistence in volatility might be overstated by structural changes in the variance equation in the context of GARCH models.

confirming Lobato and Savin (1988)). Baillie points out that the pre-war and post-1987 periods appear to be characterized by very large outliers (which raise the mean of squared returns) rather than by any fundamental change in the persistence of the volatility process. Moreover, the estimates of the long memory conditional variance parameter appear quite robust to changes in the specification of the conditional mean. Baillie et al. (2000) provide evidence that the long memory property is an intrinsic feature of the Deutchmark-US dollar spot exchange rate system rather than being due to exogenous shocks which lead to regime shifts. This is consistent with the theory that returns are a self-similar process (see Beran (1994)). On this regard, particularly important are the works of Andersen and Bollerslev ((1997), (1998)). Using the mixture of distribution hypothesis, they interpreted volatility as a combination of heterogeneous information arrivals. Although each of the information flow process exhibits short memory, the volatility process is a long memory process. Therefore, they provided evidence that the long memory characteristic of the volatility process "... constitute an intrinsic feature of the returns generating process, rather than a manifestation of occasional structural shifts" (Andersen and Bollerslev (1997), page 975).

The second reason why evidence of long memory in returns may be spurious is based on aggregation. A stock market index like the S&P500 is an aggregate index of the stock market, the (squared) returns of which are derived from the (squared) returns of the individual stocks. It may well be the case that while specific stocks do not exhibit strong dependence, the aggregate index does! A motivation of this can be found, for instance, in Robinson (1978) or Granger (1980), where it is shown that individual independent AR(1) series with random autoregressive coefficients can give rise to long memory aggregate series for certain specifications of the distribution function from which these coefficients are drawn. However, in the case of the squared return process for individual stocks, it seems quite implausible to assume independence. Moreover, Lobato and Savin (1998) found, in

general, strong evidence of long memory in the squared returns of the individual stocks comprising the Dow Jones Industrial Average. Thus, their results favor the conclusions of Ding et al. (1993). It appears that strong dependence in the second moment of asset returns is an empirical phenomenon irrespective of the sampling frequency, and cannot be attributed to aggregation.

3.2.3 Studies of Technical Trading Rules in Stock Markets

Technical analysis is not a homogeneous body of knowledge. In fact, the term “technical analysis” is a general heading for a myriad of trading techniques (Brock et al. (1992)), which involve the examination of past market data such as prices and trading volume information in an attempt to forecast future prices and, thereby, make an investment decision. Reilly and Brown (1994) categorize the different technical trading rules practiced by US technical analysts into four groups: (i) contrary-opinion rules (such as mutual fund cash positions, investment advisory opinions, future traders’ bullishness on stock index futures); (ii) follow the smart money rules (such as the confidence index, Treasury Bill Eurodollar yield spread); (iii) other market environment indicators (such as breadth of market, short interest, and block uptick-downtick ratio); and (iv) stock price and volume techniques (such as Dow theory, support and resistance levels, moving average lines, relative strength, bar charting, multiple-indicator charts, etc.). In this last group we find the technical indicators usually employed in academic studies to evaluate whether systematic economic gains accrue to the users of such indicators.

Alexander (1961) is the first to confirm the profitability of technical trading on individual US stocks. He employs “filter rules”, whereby traders buy (sell) if the price rises (falls) by more than some critical percentage. Later, Alexander (1964) finds that profitability disappears once trading costs are introduced. Fama and Blume (1966), also using filter rules and examining stock price data of thirty Dow Jones Industrial companies from

1957 to 1962, document that technical trading rules cannot be used successfully when equity costs are considered. This conclusion is reinforced by studies examining relative strength rules, which consider the strength of a share price relative to the market as a whole (see Levy (1967a,b), Jensen and Benington (1970), Bohan (1981), Brush and Boles (1983)). Van Horne and Parker (1967) conducted a series of tests where they bought (sold) a security if its current share price was greater than (less than) its average value over the previous 100, 150, and 200 days by a certain percentage. None of the 30 variations of the moving average test proved profitable when compared with a buy-and-hold strategy. James (1968) arrived at a similar conclusion when he noted that the use of monthly moving averages did not seem to offer investors any significant benefits.

Therefore, early empirical studies investigating the weak form of the EMH indicated that trading strategies based on exploiting apparent trends in historic share price data did not yield returns that were superior to a buy-and-hold strategy. However, more recent evidence suggests that technical trading rules may have some predictive ability. Sweeney (1988) examines data from 1970 to 1982 for fourteen filter rule “winner” stocks from the Fama and Blume study and suggests that substantial profits may be possible for floor traders using filter rule trading strategies even after accounting for transaction costs. Corrado and Lee (1992) examine the ability of filter rules to predict the variation in expected daily returns for a sample of 120 Dow Jones and S&P100 stocks from 1963 through 1989. The difference in returns between filter rule and buy-and-hold portfolios is eliminated by one-way transaction costs of 12 basis points. Chelley-Steeley and Steeley (1997) apply filter rules to portfolios formed with 250 UK company monthly returns data between 1976 and 1991. They document profits that are, however, sensitive to the level of transaction costs assumed, and are by and large attributable to the nonsynchronous trading among the component securities. In addition, Levich and Thomas (1993), using both filter and moving average rules, and Osler and Chang (1995) who study “head-and-

shoulders” patterns, find evidence in favor of technical indicators in currency markets. However, whether this can be translated into profits is debatable.

Novel evidence on the forecasting ability of technical trading rules which has renewed interest in academic circles regarding technical analysis has been provided by Brock et al. (1992) and Hudson et al. (1996), who employ simple moving average and trading range break rules in the US and UK respectively. The Brock et al. study analyses daily data on the Dow Jones Industrial Average (DJIA) for a 90-year period from 1897 to 1986, while Hudson et al. examine Financial Times Industrial Ordinary Index (FTI) prices over a 59.5-year period from 1935 to 1994. The message from these investigations is that the predictive ability of trading rules is uncovered if sufficiently long data series are considered. This may be the reason behind the strong support for technical analysis, unlike earlier studies. In both the US and the UK, buy signals offer positive returns whereas sell signals offer negative returns. The sell signals seem to have greater predictive ability (in statistical terms) than their buy signal counterparts. Brock et al. find that the average 10-day return based on the trading range breakout rule stands at 0.63% for buy strategies and -0.24% for sell strategies. Similar results emerge in the UK investigation by Hudson et al. - the average 10-day holding period return on buy strategies based on the trading range breakout rules is 0.70%, while the average return for sell strategies is -0.43% -. In particular, Brock et al. find that trading rule returns significantly outperform a benchmark of holding cash, though they don't closely examine whether their trading rules can be used to earn excess returns in a costly trading environment. Hudson et al. integrate transaction costs to their analysis to find that the technical rules are unlikely to yield returns over and above the buy-and-hold strategy in the UK.

Ready (1997), using intraday data for the US, finds that the Brock et al. (1992) trading rules do not beat a buy-and-hold strategy due to the trading costs and the time it takes to execute the actual trade. Bessembinder and Chan (1998) document that the

predictive ability of the Brock et al. rules is partially, but not solely, attributable to return measurement errors arising from nonsynchronous trading. Thus the economic significance of the Brock et al. study is not eliminated. Using the “double-or-out” strategy to trade on technical rule signals, they estimate “break-even” one-way trading costs to be 0.39% for the full Brock et al. sample and 0.22% since 1975, which are small compared to estimates of actual trading costs for US stocks. Gençay (1998) analyzes the DJIA index using artificial neural networks. His results indicate strong evidence of nonlinear predictability for stock market returns using moving average rules. Fang and Xu (2003) develop trading strategies that combine technical analysis and time series forecasts. They argue that while exploiting predictable components as functions of past prices or returns, technical trading rules tend to identify periods to be in the market when returns are positive, while time series forecasts are capable of identifying periods to be out when returns are negative. Employing the 10 variable-length moving average rules of Brock et al. and four autoregressive processes with different volatility specifications, Fang and Xu find that combined strategies applied to the Dow Jones Averages (Industrial, Transportation, Utilities) outperform both trading rules and time series forecasts individually.

Sullivan et al. (1999) investigate whether the results of Brock et al. are due to data-snooping biases. Data-snooping may arise from repeated examinations of the same data set, or from a subtle survivorship bias operating on the entire universe of technical trading rules that have been considered historically. Utilizing White’s Reality Check bootstrap methodology (White (2000)), Sullivan et al. carry out a comprehensive test of performance across - what they claim to be - the near universe of technical trading rules. They find that the results of Brock et al. (1992) appear to be robust to data-snooping.

The few studies that deal with the predictability and profitability of trading rules in emerging markets are evaluated in Section 3.4.1.

3.3 The Econometric Framework

3.3.1 Motivation

Contrary to the random walk hypothesis, several studies have found evidence of long horizon predictability in stock returns (Fama and French (1988), Poterba and Summers (1988), *inter alia*). Lo (1991) argues that such evidence may be symptomatic of a long-range dependent (long-memory) component in stock market prices, allowing asset returns to exhibit significant autocorrelation between distant observations.¹⁰ Consequently, many authors have tested for long memory in asset returns of developed economies, but thankfully for the proponents of the market efficiency hypothesis, met with little success (see Section 3.2.2).

Interestingly however, the studies by Barkoulas et al. (2000) and Wright (1999, 2001) report evidence of long memory in some emerging markets. This evidence suggests the possibility of differential long-term stochastic behavior between established and emerging capital markets, inviting a more thorough examination of stock return dynamics in less developed stock markets.

In contrast with findings of little serial correlation in asset prices returns, asset prices volatilities seem to exhibit a much richer structure. There is a lot of evidence that the conditional volatility of asset returns (proxied by squared, log-squared, or absolute returns) displays long memory or long range dependence (see, for example, Taylor (1986), Ding et al. (1993), Crato and De Lima (1994), Ding and Granger (1996), Bollerslev and Mikkelsen (1996), and Lobato and Savin (1998)). As a result, a non-linear model embodying the long-memory feature both in the mean and variance of returns could potentially capture adequately the statistical features of ECM return dynamics.

¹⁰The presence of long memory may give rise to consistent speculative profits that can be exploited via appropriate trading rules. For example, a significant long memory component in the conditional mean of security returns would render high-order moving average rules profitable and recommendable; otherwise, if a price series only possesses short memory, a low-order moving average rule can be recommended.

3.3.2 The ARFIMA-FIGARCH Model

The double long memory ARFIMA-FIGARCH model is the starting point in our description of the dynamic return generating process in ECM. Throughout this section we use $\{x_t\}$ to denote the price series and $\{y_t\}$ the continuously compounded returns, where $y_t = \log(x_t) - \log(x_{t-1})$.

In the spirit of Baillie et al. (2002) we parametrize the conditional mean as an ARFIMA(5,d,0) process and the conditional variance as a FIGARCH(1,δ,1) process:

$$\begin{aligned}\rho(L)(1 - L)^d(y_t - \mu) &= u_t \\ u_t &= z_t\sigma_t, \quad z_t \sim i.i.d. N(0, 1) \\ \sigma_t^2 &= \omega + \beta\sigma_{t-1}^2 + [1 - \beta L - (1 - \phi L)(1 - L)^\delta] u_t^2\end{aligned}\tag{3.13}$$

where d and δ are the long memory parameters, L is the lag operator, $\rho(L) = 1 - \sum_{j=1}^5 \rho_j L^j$, μ is the unconditional mean of the process y_t , u_t is white noise, and all the roots of $\rho(L)$ lie outside the unit circle. The lag order structure for the autoregressive component of the mean equation is chosen so as not to over-parametrize the model, while adequately describing the short-run dynamics.

It is clear that under homoskedasticity the process reduces to an ARFIMA (5,d,0) model. In general, any ARFIMA (p, d, q) model reduces to a stable ARMA(p, q) process for $d = 0$ and to the nonstationary ARIMA($p, 1, q$) process for $d = 1$. The conditional volatility dynamics follow a FIGARCH(1,δ,1) specification which imposes an ARFIMA structure on u_t^2 and implies an undefined unconditional variance for all δ . The parameter δ captures the long memory effect, while ϕ and β describe the short-run effects. The FIGARCH(1,δ,1) model nests both the stable (for $\delta = 0$) and integrated (for $\delta = 1$) GARCH(1,1) specifications. When $0 \leq \delta \leq 1$, the FIGARCH model is strictly stationary and ergodic. For a full treatment of the ARFIMA model see Granger and Joyeux (1980)

and Hosking (1981), and Baillie et al. (1996) for the FIGARCH process.

Model (3.13) can be estimated, under the assumption of normally distributed innovations, by using non-linear optimization procedures to maximize the Maximum Likelihood function below:

$$\text{Loglik}(\theta, u_t) = (-T/2) \ln(2\pi) - (1/2) \sum_{t=1}^T [\ln(\sigma_t^2) + u_t^2 \sigma_t^{-2}] \quad (3.14)$$

where $\theta' \equiv (\mu, \rho_j, d, \omega, \delta, \beta, \phi)$.

Since most returns series are not well described by the conditional normal density, the Quasi Maximum Likelihood Estimation (QMLE) technique of Bollerslev and Wooldridge (1992) is invoked to allow for asymptotically valid inference.¹¹

Starting with the ARFIMA(5,d,0)-FIGARCH(1, δ ,1) process in (3.13), we arrive at the most parsimonious representation for the returns process in each market using the general-to-specific methodology. Following the standard procedure in the literature, the truncation order of the infinite polynomials $(1-L)^d$ and $(1-L)^\delta$ is set to 1000 lags while initial conditions are set to $u_{t^*} = 0$ and $u_{t^*}^2 = E(u_t^2)$ for $t^* = 0, -1, -2, \dots, -1000$ and $t = 1, 2, \dots, T$, where T is the number of observations.

We use a number of diagnostic tests to choose between competing nested models. The first test is the Ljung-Box (Q) statistic on standardized and squared standardized residuals to test the null hypothesis of no autocorrelation up to order 50.¹² We also conduct the

¹¹Bollerslev and Wooldridge (1992) standard errors are robust against mis-specification of the shape of the conditional distributions. The consistency and asymptotic normality of the QMLE has only been established for specific special cases of the ARFIMA and/or FIGARCH model. In the context of the FIGARCH(p, δ ,q) model, detailed simulation evidence in Baillie et al. (1996) reveals that for the sample sizes typically encountered with financial data, this approximate MLE works extremely well in terms of estimating both the parameters of the process and their asymptotic standard errors. A fully general theoretical treatment however is as yet unavailable. Baillie et al. (2002) present simulation evidence to show that QMLE works quite well for estimating double long memory models.

¹²The standard portmanteau test statistic $Q_m = T \sum_{j=1, m} r_j^2$, where r_j is the j-th order sample autocorrelation from the standardized residuals and T is the number of observations, is known to have an asymptotic chi squared distribution with $m - k$ degrees of freedom, where k is the number of parameters estimated in the conditional mean. Similar degrees of freedom adjustment are used for the portmanteau test statistic based on the squared standardized residuals when testing for omitted ARCH effects.

BDS test of Brock et al. (1996) on standardized residuals to see if higher order nonlinearities are present in the stock index returns that are not captured by the model.¹³ We employ the Akaike (AIC) and Schwarz (SBC) criteria to compare the different model specifications and decide on lag order selection issues. Monte Carlo simulations show that these criteria may be effectively used in discriminating between GARCH and FIGARCH alternatives (Bollerslev and Mikkelsen (1996)).¹⁴ Finally, a robust Wald test is used to compare nested models, in particular, a stationary GARCH (1,1) specification for the conditional volatility process versus a FIGARCH (1, δ ,1) model.

3.3.3 Brakes in the Structural Breaks

Since the markets in our sample have gone through a gradual process of market integration and suffered a number of financial crises (the Asian crisis in September 1997, the Mexican peso crisis in January 1994, the Brazilian crisis in January 1999, and the Argentinian crisis in late 2001), one could argue that regime-switching and time-varying parameter models are suitable candidates for the returns data generating process in ECM. We chose not to estimate these models for the following reasons.

First, Bekaert et al. (2002) argue that regime-switching and time-varying parameter models are difficult to specify and often statistically rejected. There is no model that specifies the economic mechanism (or the dynamics involved) that moves a country from segmented to integrated status. In addition, the liberalization process itself is quite com-

¹³The BDS test attempts to distinguish between an i.i.d. series (null hypothesis) and a series with deterministic or stochastic dependence. It is calculated as

$$B_{m,T}(\varepsilon) = \frac{T^{1/2} [C_{m,T}(\varepsilon) - C_{1,T}(\varepsilon)^n]}{\sigma_{m,T}(\varepsilon)}$$

where $C_{m,T}(\varepsilon)$ is the sample correlation integral of embedding dimension m at distance ε , and $\sigma_{m,T}(\varepsilon)$ is an estimate of the asymptotic standard error of the numerator in the above equation. Under the i.i.d. null hypothesis, Brock et al. (1996) prove that $B_{m,T}(\varepsilon) \sim N(0,1)$.

¹⁴It should be noted that the use of such information criteria in ARFIMA-FIGARCH models remains to be investigated. Such an investigation, while interesting in its own right, is beyond the scope of this chapter.

plex and difficult to date, and it is unlikely that dates of capital market reforms will correspond to the true date of market integration (Bekaert et al. (2002)). For example, there are ways to circumvent capital controls through American Depositary Receipts or country funds, even though the market may be technically closed to foreign investors. In particular, the countries covered in this study were accessible to international investors around the beginning of our sample period (see Section 3.5).

Second, regime shifts or structural breaks (be they from market liberalization measures or some financial crisis) do not feature prominently in the returns series of emerging equity markets, in contrast with other financial and macroeconomic series. Bekaert et al. (2002) find it difficult to detect breaks in the U.S. dollar returns series of emerging markets using endogenous break procedures and attribute the lack of structural breaks to the noisiness of the returns series.

Third, it has been suggested that non-linear-in-the-mean models such as regime-switching or threshold autoregression models underperform simple “random-walk-type” models in explaining observed features of the data. Pagan and Sossounov (2003) have shown that a simple random walk with drift model does very well at replicating the bull and bear markets actually observed in the U.S. between 1835 and 1997, with further improvement in matching the phase characteristics when enriched with GARCH (1,1) and EGARCH (1,1) error processes. More interestingly they report that allowing for nonlinearities in the mean returns process via a hidden layer Markov-chain model adds no improvement on the results. In the context of emerging markets, Edwards et al. (2003) investigate AR(1), AR(1)-GARCH(1,1), and AR(1)-EGARCH(1,1) specifications for Argentina, Brazil, Chile, Mexico, South Korea, and Thailand. They find that during the 1990-2001 post-liberalization period, the bull phases of the emerging markets they examine are consistent with “random walk beyond a simple autocorrelation” type statistical models of returns; bear phases, though, exhibit some departures in the sense of large

negative returns at the end of the phase. Nevertheless, complicated processes such as regime-switching models or processes with stochastic volatility perform worse than the simple models they use in fitting the features of the data.

Finally, Andersen and Bollerslev (1997, 1998) argue that the long memory characteristic of the volatility process “constitute(s) an intrinsic feature of the returns generating process, rather than a manifestation of occasional structural shifts” (Andersen and Bollerslev (1997), page 975). Lobato and Savin (1998) and Baillie (1998) find little evidence of significantly time-varying long memory in long time series of the S&P500 index. Consistent with these and other studies, we regard episodes of financial market crisis as being part of the same generating process for stock returns, rather than signaling a shift to a new regime.

3.4 Technical Trading Rules and the Bootstrap

3.4.1 Previous Evidence in ECM

It is unclear in the extensive academic literature whether technical trading rules consistently outperform the benchmark strategy in developed markets (Section 3.2.3) On the other hand, a number of researchers have provided evidence that trading rules produce valuable economic signals. Much less research is devoted to emerging markets, probably due to the argument that the predictive ability of trading rules is uncovered if sufficiently long data series are considered.¹⁵ However, evidence from existing research in emerging markets suggests that the sample period length is not the important factor. Bessembinder and Chan (1995) find that the Brock et al. (1992) trading rules applied to the daily equity market indices of six Asian countries between 1975 and 1989 can be profitable, particularly in Malaysia, Thailand, and Taiwan, even when trading costs are considered. Ratner and

¹⁵For example, in both the Brock et al. (1992) and Hudson et al. (1996) studies, sub-period results generally lose significance compared to the full sample period.

Leal (1999) report strong evidence of forecasting ability for moving average rules in ten emerging equity markets in Latin America and Asia using daily, inflation-adjusted, index level returns from January 1982 through April 1995. In fact, 82 rules out of the 100 rules tested provide the correct indication of the index return change if statistical significance is disregarded. In particular, Taiwan, Thailand and Mexico emerge as markets where technical trading strategies can consistently beat the buy-and-hold after transaction costs. Strong support for the predictability of trading rules is also provided by Gunasekarage and Power (2001) in the context of four South Asian stock markets (Bangladesh, India, Pakistan, and Sri Lanka) using daily index data from 1 January 1990 to 31 March 2000, and by Parisi and Vasquez (2000) for Chile with data from 1987 to 1998. By and large, the above evidence casts serious doubt on the weak form efficiency of emerging capital markets.

3.4.2 Trading Strategy Methodology

To avoid compounding data snooping concerns, we do not attempt to exploit patterns in the data on an *ex post* basis. Instead, we apply eight Variable Length Moving Average (henceforth VMA) models and six Trading Range Breakout (henceforth TRB) rules (resistance and support levels) used by Brock et al. (1992) to index portfolios of the eight ECM, and report results from all rules. These rules appear often in previous academic research, and though subject to a survivorship bias, they were very popular with traders as of the late 1980s (Ready (2002)), often forming the basis for more complicated trading schemes.

The VMA filter involves comparison of a short-term moving average of prices to a long-term moving average.¹⁶ Proponents of such rules do not only argue that analysis of

¹⁶The moving average for a particular day is calculated as the arithmetic average of prices over the previous n days, including the current day. The test is repeated daily with the changing moving averages throughout the sample.

moving averages helps identify trends in the series, but also that computation of moving averages smooths out an otherwise volatile series. A VMA (S, L, B) rule simulates returns from a strategy where the investor goes long as the short (S-day) moving average of prices moves above the long (L-day) moving average by an amount bigger than B% of the L-day average (buy signal), and stays in the market until the S-day falls below the L-day moving average by more than B% (sell signal). Upon a sell signal the investor is out of the market (or sells, if he has previously bought the index), *not* short. Our trading rules do not generate short sell signals as many emerging markets have short selling restrictions.¹⁷ No signal is generated when the short moving average is inside the band B. The band is designed to reduce the number of trades caused by frequent whipsaws in the price series during non-trending markets. With a band of zero all days are classified into either buys or sells. As in Brock et al. (1992) we test some of the most popular rules; 1-50, 1-150, 5-150, 1-200, with and without a band of 1%, making for eight moving average combinations in total. The variations avoid omitting any signal or phenomenon due to the particular features of each rule.

TRB rules emit buy (sell) signals when the current price moves above the recent maximum (below the recent minimum), where maxima and minima are defined over some previous days and represent local resistance and support levels respectively. Brock et al. (1992) actually evaluate TRB rules where the recent maximum or minimum values are based on the past 50, 150, and 200 days. Each of these is evaluated with and without a 1% band, making for six TRB rules in total. Again, we do not experiment with the holding period and the band percentage to avoid data mining. As in Brock et al., for this rule we compute 10-day holding period returns following buy and sell signals, ignoring other signals occurring during this 10-day period. This contrasts with VMA rules, whereby positions taken in response to buy and sell signals are held until the signal ceases.

¹⁷Of the countries covered in this study only Argentina, Thailand and Indonesia allow short selling by foreign institutions.

It should be noted that both types of rules are trend-following, positive reinforcement (or momentum) strategies, which take advantage of positive serial correlation in equity returns; traders potentially profit from use of these rules if prices continue to move in the same direction as the price change that initiated a signal. We adopt the t-statistics used by Brock et al. (1992) to test the null hypothesis that mean returns generated by technical trading rules equal the returns derived by the buy-and-hold strategy.¹⁸ In particular, significant differences in average buy-sell equity returns following trading rule signals demonstrates the effectiveness of the rules to forecast equity returns in emerging markets.

As we are also interested in the profitability of the technical trading rules to a trader who implemented the signals during the sample period in each market, we consider a “double-or-out” scheme by which a trader simply holds our index portfolio in the absence of a trading signal, liquidates the portfolio in favor of Treasury bills (T-bills) in response to sell signals, and borrows at the risk-free (T-bill) rate to double the equity position in response to buy signals.¹⁹ Note that the strategy is not at odds with short-selling practices in emerging markets. Brock et al. (1992) and Hudson et al. (1996) assume that if the number of buy and sell signals is approximately similar, the risk exposure

¹⁸For the buy and sell returns, the t-statistic for the null hypothesis that the mean buy and sell returns are not statistically different from the unconditional returns in each market is:

$$\frac{\mu_r - \mu}{(\sigma^2/T + \sigma^2/N_r)^{1/2}}$$

where μ_r and N_r are the mean return and number of signals for the buy and sells respectively, μ is the unconditional mean, T is the number of observations and σ^2 is the estimated unconditional variance for the entire sample. For the buy-sell difference the t-statistic for the null hypothesis of equality with zero is

$$\frac{\mu_b - \mu_s}{(\sigma^2/N_b + \sigma^2/N_s)^{1/2}}$$

where μ_b and μ_s are the mean returns for the buys and sells respectively, and N_b and N_s are the number of signals for the buys and sells.

¹⁹As in previous studies (Besembinder and Chan (1988), Ready (2002), Fang and Xu (2003)), we assume that one can borrow at the risk-free rates corresponding to Treasury Bills. However, as noted by Fang and Xu (2003), since the Treasury doesn’t engage in margin transactions, call margin rates would probably be a more appropriate borrowing measure. If this is the case the borrowing rate is likely to be only slightly higher than the T-bill rate for the time period covered in this study.

of employing the strategy approximates the risk of a buy-and-hold strategy, so that the two strategies should produce similar returns. They thus restrict the investor to an equal number of buy and sell positions irrespective of the actual number of buy and sell signals.²⁰ Bessembinder and Chan (1988) consider actual buy and sell positions as signaled by the trading rules, noting that the overall risk borne by a trader applying the “double-or-out” strategy is quite similar to the risk of buy-and-hold returns. Similarly, we investigate whether “double-or-out” excess returns come at the expense of unduly higher risk.

We measure the improvement (before transaction costs) in the trader’s accumulated return due to using each technical rule instead of a buy-and-hold strategy as follows. Let R_t denote the day t return on the index and r_t denote the day t risk-free interest rate. The excess return earned by applying trading rule i on day t - π_{it} - in the context of the “double-or-out” strategy is: (i) $(R_t - r_t)$ if trading rule i yields a buy signal on day $t - 1$, (ii) 0 if there is no trading signal, and (iii) $(r_t - R_t)$ upon a sell signal on day $t - 1$. If π_i^B is the sum of π_{it} across buy days, $N(\text{buy})$, and π_i^S is the sum of π_{it} across sell days, $N(\text{sell})$, then $\pi_i = \pi_i^B + \pi_i^S$ is the total excess returns over the sample period.²¹ We also compute *one-way* break-even costs - C_i - to determine the level of transaction costs that would just eliminate the ex post difference between cumulative returns to traders using the technical rules versus those who buy and hold the indices. These are calculated as $C_i = \pi_i / 2N(\text{trading})_i$, where $N(\text{trading})$ is the number of days when new trading signals arrive to “switch” the position from “double” to “out” or vice-versa, thus incurring transaction costs. The factor 2 in the denominator of C_i is due to the design of the “double-or-out” strategy, and accounts for the reversals of positions when a rule

²⁰Ready (2002) notes that as the “double-or-out” approach involves doubling the equity investment on buy days, financing 50% of the *total* investment by selling bonds, any trading rules with more buy days than sell days will tend to yield positive excess returns compared to the unlevered position in equity.

²¹The computed returns actually apply to any symmetric strategy in which the investor responds to buy signals by increasing the equity position by a given percentage, and responds to sell signals by decreasing the equity position by the same percentage. We could have also evaluated asymmetric strategies where reactions to buy and sell signals differ. However, as Bessembinder and Chan (1998), we refrain from doing so to avoid increasing the danger of data-snooping biases potentially induced by a wider search over different trading strategies.

ceases to emit a signal (not counted in $N(\text{trading})$).²²

Finally, there is a growing consensus among financial economists that nonsynchronous trading of component securities induces spurious positive serial dependence in portfolio or index returns (Scholes and Williams (1977), Lo and Mackinlay (1990b)). Since the technical rules we consider rely on positive serial dependence, any apparent success may reflect return measurement errors. Therefore, we investigate the sensitivity of returns to implementation of a one-day lag, in which, technical trading returns are measured with reference to the closing index value one day after a trading signal is initiated. Omitting the first day return eliminates the bias in measured returns attributable to nonsynchronous trading if each security trades during the intervening day. This is not an unreasonable assumption as our indices are composed of large and liquid securities.

3.4.3 The Bootstrap Methodology

The purpose of employing bootstrap methodologies in concert with technical trading rules is threefold. First, it is possible to investigate whether the specified statistical processes for the generation of stock returns in ECM can reproduce technical trading rule results consistent with the actual data. In other words, the actual trading rule results act as a specification test for the underlying process (Brock et al. (1992)).²³ Second, utilizing empirical distributions of returns and prices augments technical analysis and standard statistical procedures by addressing important aspects of the data such as skewness, kurtosis, autocorrelation and conditional heteroskedasticity, and can thus be used to gauge the significance of trading rule results more “accurately” than t-ratios

²²For more information on the design and implementation of the “double-or-out” scheme consult Bessembinder and Chan (1998).

²³Brock et al. (1992) find that trading rule profits on the Dow Jones Industrial Average are not consistent with a random walk model, an autoregressive model of order 1 (AR(1)), a GARCH-in-mean model (GARCH-M), or an exponential GARCH (EGARCH) model. In other words, the predictability generated by the aforementioned popular null models for stock returns are not consistent with the predictability uncovered in actual data by technical trading rules.

which assume normal, stationary, and time-independent distributions. A third benefit of this methodology is that we can examine the standard deviations of returns during buy and sell periods, which provides an indication for the riskiness of the trading strategies within the sample period relative to the buy-and-hold benchmark.

The application of the bootstrap methodology in combination with technical analysis is not particularly new to the finance literature.²⁴ In the spirit of Brock et al. (1992), Ito (2003), and Kho and Karolyi (2004), we investigate whether the estimated ARFIMA-FIGARCH models for the eight ECM are in agreement with, or rejected by, the trading rule results. Our methodology differs from previous studies in developed markets in that we incorporate the stochastic properties of both the mean and volatility of the original returns series.

We use the model-based bootstrap methodology inspired by Freedman (1981, 1984), Freedman and Peters (1984a,b), Efron and Tibshirani (1986, 1993), as well as the application in Andersson and Gredenhoff (1998) who bootstrap autoregressive and heteroskedastic models. Since the data generating processes of stock returns are well specified stationary statistical models, it is only natural to use a model-based bootstrap that maintains dependencies in the data and is able to generate new bootstrap stationary pseudoseries.²⁵

Our bootstrap procedure consists of 500 replications for the selected model for each market. In each replication the re-centred standardized residuals \hat{z}_t (demeaned residuals divided by their estimated standard deviation) for each model are redrawn with replacement from the degrees of freedom corrected residual vector to form a scrambled

²⁴ Apart from Brock et al. (1992), Levich and Thomas (1993), Bessembinder and Chan (1998), Ratner and Leal (1999), and Ito (2003), also employ the bootstrap procedure. Applications vary however. Levich and Thomas (1993) and Ratner and Leal (1999), for example, follow the standard approach of reshuffling the original returns series to form bootstrap samples which resemble the original in terms of distributional properties but destroy any serial dependencies. Under the null hypothesis of no abnormal performance, the profit obtained with the actual series should not differ from profits obtained with the shuffled series. This deviates from the application in this study which generates predictability according to the chosen model and evaluates whether that is consistent with actual trading results (as in Brock et al. and Ito).

²⁵ A model free procedure, such as a moving blocks bootstrap, may also preserve dependencies. However, model free approaches deviate from the bootstrap testing idea of Davidson and Mackinnon (1999), in the sense that resemblance between the bootstrap samples and the original sample is sacrificed.

(standardized) residual series:

$$\bar{z}_t = \sqrt{\frac{T}{T-k-1}} \hat{z}_t, \quad (3.15)$$

where k is the number of estimated parameters in the mean equation. This non-parametric resampling scheme does not impose distributional assumptions and allows the scrambled standardized residuals to deviate from Gaussianity.

The bootstrap residuals (\bar{u}_t) are then built by imposing the *estimated* conditional dependency according to the preferred specification:

$$\bar{\sigma}_t^2 = \hat{\omega} + \hat{\beta} \bar{\sigma}_{t-1}^2 + \left[1 - \hat{\beta}L - (1 - \hat{\varphi}L)(1 - L)^{\hat{d}} \right] \bar{u}_t^2 \quad (3.16a)$$

and

$$\bar{u}_t = \bar{z}_t \sqrt{\bar{\sigma}_t^2} \quad (3.16b)$$

where the hats above coefficients indicate estimated parameters.

Next, the bootstrap return series \bar{y}_t are created recursively by the equation

$$(\bar{y}_t - \hat{\mu}) = \hat{\rho}(L)^{-1} (1 - L)^{-\hat{d}} \bar{u}_t \quad (3.17)$$

where $\hat{\rho}(L)$ and \hat{d} are the *estimated* autoregressive polynomial and long memory in-the-mean parameters, respectively. The returns series are then exponentiated back into a price series.

In order to account for possible initial-value effects and for the fact that long memory processes require a large number of observations to exhibit the hyperbolic decay of their autocorrelations, we carry out the above procedure by generating $T+500$ observations, the *first* 500 of which are then removed.²⁶

²⁶We test the sensitivity of our results by also generating $T + 1000$ observations (in each replication) and we find that the impact on the results is insignificant.

Finally, we generate distributions for the buy, sell, buy-sell returns, and standard deviations of buy and sell statistics under the simulated null models for each market, by applying each and every VMA and TRB strategy tested on actual data and on the simulated samples as well.²⁷ The hypothesis that trading rule results from the observed data are consistent with statistics from the simulated data is rejected at the α percent level if statistics from the actual indices used are greater than the α percent cutoff of the simulated returns under the adopted models.

3.5 Data

The data set consists of Morgan Stanley Capital International (MSCI) daily stock index prices which do not include dividends from 01/01/1988 to 31/05/2002 - a total of 3761 daily observations - for eight emerging markets which can be grouped into two geographical regions: Latin America (Argentina, Brazil, Chile, Mexico) and Asia (Indonesia, Philippines, Taiwan, Thailand).²⁸ The MSCI indices are constructed to provide benchmarks that accurately represent the opportunities available to the institutional investor. It is estimated that over 90% of international institutional equity asset holdings in the US are benchmarked to MSCI indices.²⁹ The market indices are consistently computed across different markets and are therefore directly comparable. The component securities are free float adjusted and screened by size and liquidity. Indices are constructed so as not to double-count those stocks multiple listed on foreign exchanges. MSCI used to target 60% of the free float adjusted market capitalization in each industry group, thus

²⁷Note that extending the number of replications beyond 500 adds very little to the reliability of estimated p-values of the trading rule statistics.

²⁸The markets examined in this study have a relatively high proportion (measured by value) of daily trade by foreigners. For example, in Thailand and Indonesia the proportion of daily trade by foreigners averaged 43% and 52% respectively in 1997, while in Korea and Malaysia it was only around 7% (source: S&P Emerging Market Fact book and IMF), reflecting the aggressive local trading nature of the latter markets.

²⁹www.msci.com

capturing 60% of the total country market capitalization while accurately reflecting the economic diversity of the market (that percentage has been raised to 85% since November 2001). In particular, the MSCI “Free” indices we use are designed to fully reflect investable opportunities for international institutional investors, by taking into account local market restrictions on share ownership by foreigners.³⁰ The S&P/IFC Investable Indices are directly comparable, but date back only to October 1995 on a daily basis. To the best of our knowledge, MSCI (daily) emerging market data have not been used in previous academic research.

As reported in Bekaert and Harvey (2000), official liberalization dates for the countries concerned are clustered in the late 1980s - early 1990s period. Nevertheless, markets were accessible to foreign investment prior to 1988 through country funds, except for Argentina (the first country fund was introduced in October 1991),³¹ Chile (September 1989), and Indonesia (January 1989). Another indicator of the “degree of liberalization” is a measure of the intensity of capital controls as in Edison and Warnock (2003). At around the start of our sample period, foreign ownership restrictions in Asian countries were quite high, declined over the course of the 1990s, and were greatly relaxed during the 1997/1998 Asian financial crisis. The Latin American countries, however, opened up to foreign investment far earlier and far more extensively than their Asian counterparts. Edison and Warnock’s measure suggests that Argentina’s equity market was almost completely open to foreign investment before our sample started, Mexico opened its market by 1990 and Brazil followed shortly thereafter. Chile relaxed its controls in the early 1990s, but instituted controls in the mid-1990s against short-term flows.

Throughout this study we focus on dollar denominated series since this is presumably

³⁰These restrictions, as detailed on Morgan Stanley’s website may have assumed several forms: (1) specific classes of shares excluded from foreign investment; (2) specific securities or classes of shares for an individual company may have had limits for foreign investors; (3) the combination of regulations governing qualifications for investment, repatriation of capital and income, and low foreign ownership limits may have created a difficult investment environment for the foreign investor; and (4) specific industries, or classes of shares within a specific industry, may have been restricted to foreign investors.

³¹Note, however, that the official liberalization date for Argentina is November 1989.

most relevant for international investors, and because local currency returns are very erratic due to occasional bursts of hyperinflation in some emerging markets, especially Argentina and Brazil.

Finally, the daily US Treasury bill yield series between 01/01/1988 to 31/05/2002, employed in the “double-or-out” strategy test, is obtained from Kenneth French’s website.

3.6 Empirical Results

3.6.1 Summary Statistics

Tables 3.1 and 3.2 report summary statistics for one-day and 10-day (non-overlapping) US dollar returns of the Asian and Latin American markets respectively. The buy-and-hold strategy (unconditional) returns over the whole sample period are higher in the Latin American countries (ranging from 8.0% annualized in Argentina to 20% in Mexico) than the Asian markets (from -1.1% in Thailand to 5.1% in Taiwan), and do not seem to come at the expense of higher risk (excluding Argentina). The Asian market daily returns exhibit positive skewness, while Latin American market returns are negatively skewed. This difference in skewness may partly be attributed to the Latin American economies being more integrated than the Asian markets over our sample. Bekaert et al. (1998) note that when integration brings about stock market development that leads to more companies seeking a stock market listing and eventually a more diversified index, skewness (and kurtosis) may decrease. Stock index returns from all markets are found to be leptokurtic (Tables 3.1 and 3.2 show excess kurtosis). The Jarque-Bera normality test indicates that all the eight returns series are not normal (p-values in brackets). These findings are in agreement with other emerging market studies (e.g. Bekaert and Harvey (1997), De Santis and Imrohoroglus (1997), Choudry (1996)), and point to similarities in the distribution of returns for both developed and developing markets. Augmented Dickey-Fuller (ADF)

tests indicate that stock returns are generated by stationary stochastic processes.

Autocorrelation statistics for daily returns are only significant for short lags in all cases. However, squared returns have many lags of significantly positive sample autocorrelations, particularly for the Asian markets, which are bigger in absolute value than the corresponding returns autocorrelations. This suggests that short-memory models are probably adequate for capturing dynamics in the conditional mean, while conditional volatility exhibits a more persistent autocorrelation structure.

3.6.2 Econometric Results

In Table 3.3 we present the results of estimated parsimonious specifications of the ARFIMA-FIGARCH model (3.13) for each country. In all markets, we fail to reject the null of no fractional integration in the conditional mean.³² This is in contrast with the studies by Wright ((1999), (2001)) and Barkoulas et al. (2000) which report some evidence in favor of long memory in emerging market stock returns.³³ Instead, we find that conditional mean dynamics seem to be characterized by non-trivial low-order autoregressive components. These results add to the mounting evidence of positive persistence of ECM returns and are in line with Bekaert (1995) who suggests that, in emerging markets, it is often possible to predict future returns using only lagged returns.

As far as conditional volatility dynamics are concerned, the fractional differencing parameter in the volatility (δ) is significantly different from zero in all markets, implying fractional integration. Note that δ is always in the stationary region (between 0

³²We recognize that the span of the data is important for long-memory inference. For this reason, and before making a final inference for the significance of d , we experimented with both autoregressive and moving average parameters in the conditional mean equation, and with no long memory in the conditional variance to avoid the possibility of over-parametrizing our model. We found that including δ does not affect the inference on d .

³³Both Wright (1999) and Barkoulas et al. (2000) use the Geweke and Porter-Hudak estimator (1983) which is not robust to short-run dynamics. Although Wright (2001) employs the ARFIMA model to find some evidence in favor of long memory, he does not model conditional volatility dynamics at all, thus not accounting for the impact of heteroskedasticity on the standard errors of his coefficient estimates.

and 1). The Q statistics and the model selection criteria (AIC/SBC) favored the FIGARCH to either the GARCH (1,1) or IGARCH (1,1) error specifications. In addition, a robust Wald test for the null hypothesis of a stationary GARCH(1,1) model versus a FIGARCH(1, δ ,1) gave numerical values ranging from 51.89 in Philippines to 429.93 in Indonesia, providing overwhelming rejections of the GARCH(1,1) formulation in all markets. The Q statistics of the preferred model specifications in Table 3.3 fail to reject the null hypothesis of no autocorrelation in the standardized and squared standardized residuals. Also, the BDS test statistic on the standardized residuals does not produce significant evidence against the null hypothesis of identically and independently distributed residuals.³⁴ The preferred models for the Asian markets are: AR(1) - FIGARCH(1, δ ,1) for Philippines, AR(3) - FIGARCH(1, δ ,0) for Taiwan, AR(2) - FIGARCH(1, δ ,0) for Indonesia, AR(2) - FIGARCH(1, δ ,0) for Thailand. For the Latin American markets: AR(1) - FIGARCH(1, δ ,0) for Mexico, AR(2) - FIGARCH(1, δ ,0) for Chile, AR(1) - FIGARCH(1, δ ,1) for Brazil, and AR(3) - FIGARCH(1, δ ,1) for Argentina.³⁵ It should be noted that the conditions for the conditional variance to be positive are always satisfied for the chosen models.³⁶

3.6.3 Trading Rule and Bootstrap Test Results

Trading rule returns are presented for Asian and Latin American markets in Tables 3.4 and 3.5 respectively. The rows labeled “Buy” and “Sell” present the quantities $\pi_i^B/N(\text{buy})$ and $-\pi_i^S/N(\text{sell})$ respectively, where π_i^B and π_i^S are excess returns, and $N(\text{buy})$ and $N(\text{sell})$ are the numbers of buy and sell signals generated by each rule. The difference between

³⁴Following Baillie et al. (2000), for robustness purposes, m was chosen to be in the range 2 through 10, while ε was fixed in the range of 0.25s through 1.25s, where s is the standard deviation of the data. Detailed results are available upon request.

³⁵Detailed results on the different model specifications are not presented to conserve space. They are available upon request.

³⁶Bollerslev and Mikkelsen (1996) derive sufficient conditions for the case of a FIGARCH (1, δ ,1) process: $\beta - \delta \leq \phi \leq \frac{1}{3}(2 - \delta)$, and $\delta (\phi - \frac{1}{2}(1 - \delta)) \leq \beta (\phi - \beta + \delta)$. Positiveness of the conditional variance was also checked on a country-by-country basis.

“Buy” and “Sell”, denoted as “Buy-Sell”, can be realized by executing the buy and sell signals (as, for instance, in the “double-or-out” strategy). The statistical significance of trading rule returns is first evaluated using standard t-tests (see expressions in footnote 18). Note that the significance of mean buy and sell returns of TRB rules is gauged against the unconditional 10-day return. Throughout, we only present results with the nonsynchronous trading correction which are slightly more conservative than returns without the one-day lag correction.³⁷ Our results show that the predictability in emerging markets cannot be attributed to nonsynchronous measurement biases.

For the trading rule to be effective, the average buy return must be significantly larger than the average sell return. Out of 64 VMA rules tested in all emerging markets (eight countries with eight models each), 48 models (i.e. 75% of the models) have buy returns significantly larger than sell returns according to standard t-ratios at the 10 percent significance level. *All* VMA modes applied to Asian countries produce significant buy-sell spreads (apart from the (5,150,0) rule in Thailand), which exceed by far the average unconditional one-day returns. This suggests that the evidence of predictability is not specific to the size or age of market studied. The Latin American markets account only for 17 (out of the 48) significant buy-sell differences (35%), and seven of them are concentrated in Chile alone. Thus VMA rules uncover a higher degree of predictability in Asian than in Latin American markets. A major part of the predictive content of the VMA rules in Asian markets offers negative returns: average sell returns for almost all rules are significant and usually bigger in absolute value than corresponding buy returns. With the exception of Philippines, average buy returns are significant for the two shorter length rules only: (1,50,0) and (1,50,0.01). In Latin American markets, buy and sell signals seem to be equally powerful for predictive purposes, though fewer rules exhibit significant

³⁷ There are some significant discrepancies between TRB rule results with and without the one-day lag correction in some markets. This is because there is a small number of buy and sell days compared to VMA rules. The one-day lag before a trade takes place and the fixed-length 10-day holding period after each signal imply that 20% of the rule returns are different when one compares non-synchronous adjusted to non-adjusted results.

buy/sell returns than in Asian countries; only the (1,50,0) and (1,50,0.01) average buy and sell returns are significant in Mexico and Brazil, while Argentina does not exhibit significant buy or sell returns at conventional levels (though significant buy-sell spreads are recorded for the two “faster” rules).³⁸ Also, in absolute value, buy returns exceed sell returns on average in Latin America.

It should also be noted that the (1,50,0) and (1,50,0.01) rules exhibit much higher returns compared with the other strategies in all markets, with the (1,50,0.01) rule yielding the largest return. In general we observe that increasing the length of the long moving average, all else equal, reduces the buy-sell spread; increasing the length of the short moving average, all else constant, also causes a decline in buy-sell return. The introduction of the 1 percent bandwidth increases the buy-sell spread for the majority of VMA models. The analysis of the different technical rules therefore indicates that the rigorous selection of long moving average, short moving average, and bandwidth, can increase the potential profitability of the strategy even further.

As far as TRB rules are concerned, 29 out of a total of 48 rules (60%) identify significant buy-sell differences, again with Latin America exhibiting the smaller share (11 rules or 38 % of the total). Results confirm the significant predictability uncovered in Asian markets by VMA rules, excluding Thailand, which exhibits only one (weakly significant) buy-sell spread with TRB rules. TRB results reinforce the finding of no predictability in the Argentinian market, while there is only 1 weakly significant return in the Brazilian market. On the contrary, significant predictability - even exceeding that in Chile - is uncovered in the Mexican market, with an average 10-day rule buy-sell return only less to Taiwan's and Indonesia's. In agreement with VMA rule results, Indonesia is the most profitable market based on the TRB rules average buy-sell return.

Taken together, 77 out of the 112 technical rules (69% of the total) produce buy signal

³⁸This evidence is rather consistent with Urrutia (1995), who finds that the null hypothesis of a random walk in stock returns is rejected for Brazil, Chile, and Mexico, but not for Argentina.

returns which are not only positive, but also statistically different from the corresponding negative sell signal returns, demonstrating profit potential in emerging markets. In addition, when we examine only the average returns of the buy and sell signals, disregarding their statistical significance, we see that 110 out of the 112 rules examined in this paper contain average buy signal returns greater than the sell signals. Technical trading strategies are almost always correct in predicting the direction of change in the returns series in emerging markets; though profitability is not guaranteed, investors or firms interested in market timing may still use the information conveyed by technical trading rules.³⁹

When we consider the significance of the buy-sell spread relative to the simulated model for each market, the degree of trading rule predictability drops, particularly for the VMA rules. Tables 3.6 and 3.7 report the fraction of simulations producing a rule statistic at least as large as that from the original Asian and Latin American market returns series for VMA and TRB rules respectively. This number can be thought of as a simulated “p-value”. The statistics of interest are average buy and sell returns, buy-sell return, and standard deviations of buy and sell returns. Focussing on the buy-sell rows, the number of “significant” (at the 10 percent level) buy-sell statistics drops from 48 to 25, out of the total of 64 VMA rules (39% of the total). Latin American markets only account for 2 of these 25 significant models, *both* found in the Chilean results. When considering significance relative to the simulated distribution at the 5 percent level, p-values reveal that on aggregate only 10 VMA rule buy-sell returns cannot be explained by the simulated series. Therefore, the predictability generated by the simulated returns generating processes seems to explain, at least partially, the predictability in actual index data for VMA strategies, particularly in Latin American countries. However, the simulated statistical models are not as successful in replicating TRB rule buy-sell spreads;

³⁹Ready (2002) notes that forecasts from technical analysis may be useful for firms which have substantial flexibility in the timing of secondary issues, as offerings are more likely to be successful during a rising market. Bessembinder and Chan (1998) argue that a Bayesian investor could alter his asset allocation in response to this information, even if they could not profit from the *buy-sell* signals.

the percentage of “significant” TRB rules drops only slightly to 56% (27 rules), with Latin American markets exhibiting the same share of such rules as with standard t-tests (10 rules out of the 27 (37%)).⁴⁰

The lower predictive performance of technical trading rules in Latin American as opposed to Asian markets, verified both with standard and bootstrap statistical techniques, may be a natural consequence of the more extensive financial liberalization process the Latin American countries have undergone, leading to openness and efficiency of asset prices. Indeed, Edwards et al. (2003) suggest that post-liberalization the stock market fluctuations of Latin American countries resemble those of developed economies, with lower volatility and amplitude of both “bull” and “bear” phases. Asian markets, however, have become more dissimilar to developed economies in the 1990s, with stock market fluctuations more like those of the pre-1990s Latin America (i.e. large amplitude and volatility of cycle phases). Note that before financial liberalization the shape of stock market cycles in both Latin American and Asian countries revealed significant predictabilities, with returns exhibiting “acceleration” patterns near peaks or troughs, thus signaling the possible existence of inefficiencies. One would expect that in the past decade stock markets in the two regions would, at least, not behave in an opposite way, as all countries were subjected to financial liberalization measures, even though to a different extent and degree. Edwards et al. attribute this difference in stock market behavior to the profound influence of the Asian crisis on Asian markets. We explore the effects of the Asian crisis on our trading rule results in Section 3.6.4.

Among the Latin American markets, trading rules generally pick more persistence in Chile, with a pattern of results rather resembling that from Asian markets. Chile thwarted short-term foreign investment in 1995 by re-imposing capital controls. Edwards et al. (2003) note that the concordance of stock market cycles between Chile and the

⁴⁰TRB rule results must be looked upon with some degree of caution, since, given the 10-day holding period after signals and the relatively short sample period, the number of buy and sell signal returns are much less than those of VMA rules.

other three Latin American countries only begins to increase well after the Asian crisis, while, on the other hand, there are some signs of concordance with Thailand. Of course, microstructure issues at the country level may also explain the results reported here; for example, Chile is known to be a highly concentrated and illiquid market (Parisi and Vasquez (2000)), forming a welcoming environment for technical analysis to be useful.

Tables 3.8 and 3.9 summarize results across all rules using a simple average: The “Simulation Mean” rows refer to the returns and standard deviations for buy signals, sell signals, and buy-sell spreads, averaged over the 500 simulated series for each market. These can be compared with the corresponding statistics from the actual index series.

For the Asian markets, the VMA rules average buy-sell p-values indicate that the underlying statistical returns model cannot be rejected at the 5% significance level in the Phillipines, Thailand, and Indonesia, and at the 1% level in Taiwan. Both the individual rule (Tables 3.6-3.7) and rule average (Tables 3.8-3.9) p-values show that buy returns from the technical strategies are generally better replicated by the simulated models than sell returns.⁴¹ This indicates that even when evaluated with non-normal distributions, sell signal returns have higher predictive power in Asian markets than buy signals. Our finding is consistent with evidence from Edwards et al. (2003) regarding the ability of “simple” returns processes to capture bull phases in emerging markets more adequately than bear phases. Furthermore, the simulated models do a good job in tracking both buy and sell volatilities (the lowest rule-average p-value recorded is 0.082 for the VMA sell standard deviation in Taiwan). In particular, the buy return standard deviations are better replicated than corresponding sell volatilities in Taiwan, Thailand, and Indonesia, as indicated by the p-values and also by the fact that average simulated buy return volatilities are closer to their actual values than simulated sell volatilities are to their corresponding values from the index series.

⁴¹ Observe that, in most cases, p-values for buy returns exceed one minus the p-value of the corresponding rule sell returns.

It is important to note that, in agreement with developed market results, sell signals pick periods of higher volatility than buy signals in Asian markets since the average sell standard deviation across all VMA rules is higher than the average buy standard deviation. Given that sell signals also pick periods of lower conditional means than buy signals, it is evident that high volatility periods are associated with lower conditional means than low volatility periods. Moreover, since sell signals actually relate to negative excess returns that account for a large fraction of trading days,⁴² they cannot be explained away by seasonalities. Thus, a rationalization of stock returns predictability in terms of time-varying risk premia in the context of equilibrium models is problematic.⁴³

In Latin American markets the simulated models replicate quite successfully conditional mean and volatility dynamics across all rules, with p-values much higher than conventional significance levels. Moreover, a simple comparison of actual and simulated VMA rule averages suggests that trading rule statistics are not different from those of market index data. In contrast to Asian markets, buy and sell returns are equally well explained by the statistical processes, apart perhaps from Chile where sell returns (average p-value 0.668) appear to be better replicated than buy returns (average p-value 0.092). Similarly to Asian markets, sell signals select periods of lower return and higher volatility than buy signals do. In addition, the simulated models in Latin American markets produce a spread between buy and sell volatilities in favor of the latter, consistent with actual data.

Table 3.9 shows that for the average TRB rule, bootstrap tests cannot reject the null hypothesis of equal buy-sell returns in actual and simulated data at the 1% level in

⁴²See the N(sell) row in Table 3.12.

⁴³The omission of dividends from the MSCI stock index series is not expected to have much effect on measures of the buy-sell spread or on tests of whether the technical rules possess forecast power (Bessembinder and Chan (1998)). However, Bessembinder and Chan find that adding the dividend yield on the Dow Jones Industrial Average renders negative point estimates of returns during technical sell signals economically small and statistically insignificant. Thus they conclude against rejecting the equilibrium implication that the market risk premium is non-negative. MSCI provides dividend-reinvested indices for emerging markets -on a daily basis- only since 2001.

all markets except Taiwan. The simulated $AR(2)$ -FIGARCH($1, \delta, 0$) process in Thailand seems to fit the TRB rule returns even better than the VMA returns. In contrast with VMA rule results, average buy-sell spreads are “significant” at the 5% level in Mexico and Chile. Note, however, that individual rule buy and sell returns are rather well replicated by the simulated series, particularly for Mexico. For Argentina and Brazil, inferences from TRB rule bootstrap returns agree with VMA results. As with VMA rules, the volatility dynamics of TRB rule returns in all markets are adequately explained by the simulations - the lowest p-value being 0.940 for the buy return volatility in Mexico - providing robust evidence for the success of the FIGARCH volatility process.

3.6.4 Effects of the Asian Crisis

As we have argued in Section 3.3.3, we have taken the view that ex post documented episodes of financial market crisis are parts of the same generating process for stock returns rather than a shift to a new regime. However, due to the magnitude and significance of the Asian crisis, it may be worthwhile to investigate whether the forecasting ability of trading rules in Asian stock markets is driven by the sizeable (negative) return outliers observed during such troubled period. Using the VMA strategies, which produce a much larger number of signals than corresponding TRB rules, we report VMA rule returns ignoring the signals and subsequent returns that have occurred during the crisis period. The Asian crisis period is identified as: 2 July 1997 to 30 September 1998 for Thailand (see, for example, Kamesaka and Wang (2003)), 11 July 1997 to 30 September 1998 for Philippines, 4 August 1997 to 6 October 1998 for Indonesia (Kamesaka and Wang (2001)), and 17 October 1997 to 30 September 1998 for Taiwan. The start dates of the crisis in each country correspond to the currency floating dates. Results appear in Table 3.10 and can be compared with VMA results for the full sample from Table 3.4.

It is evident from Table 3.10 that the VMA rules average buy-sell spread declines

across all Asian countries - apart from Taiwan - once the crisis period is excluded from the analysis. This is a direct result of the decrease in the (absolute) sell returns recorded for each rule, as during the excluded period higher (in absolute value) sell returns were recorded than either in the period before or after the crisis. Buy returns, on the contrary, are either marginally higher or equal to the returns for the full sample; they are equal if no buy signal was generated by the technical rule during the crisis period, which is particularly the case for Indonesia. The statistical significance of sell returns across all countries and almost all rules declines considerably compared to the full sample (actually excluding the (1,50,0) and (1,50,0.01) sell returns, most other sell returns are now insignificant), even though the significance of buy-sell spreads is adversely affected only in Indonesia (for half of the rules). This adds to the fact that the buy-sell spread in Indonesia is down by about 34% from the corresponding full sample average, indicating that Indonesia was the hardest hit by the crisis of all countries studied. On the other hand, the results for Taiwan exhibit no significant difference compared with the full sample. This is because the stock market and exchange rate of Taiwan were affected to a lesser degree than those of other Asian countries during the turmoil; though the MSCI Taiwan index dropped by about 34% in U.S. dollar terms, it compares favorably with U.S. dollar drops of around 70% for the MSCI Philippines, 75% for the MSCI Thailand, and 93% for the MSCI Indonesia indexes.

Overall, although excluding the Asian crisis period from the analysis reduces buy-sell returns from following the trading rule signals, the statistical significance of buy-sell spreads still demonstrates higher predictability of technical analysis for Asian than Latin American markets.

3.6.5 “Double-or-Out” Strategy Results

Tables 3.11 and 3.12 report the full-sample results of the “double-or-out” trading strategy employing signals from VMA and TRB technical rules respectively; results for a foreign investor who did not trade during the crisis period are also reported for Asian markets and VMA rules only. The N(Buy) and N(Sell) rows refer to the number of buy and sell signals generated by each rule, while N(trading) is as defined in Section 3.4.2 and is obviously much less than N(buy) and N(Sell) for VMA rules.

In Asian markets there is no strong, consistent evidence in favor of either bullish or bearish markets using buy and sell signals of VMA and TRB rules. This can be attributed to the high sensitivity of these markets to local, regional, and global events (Gunasekarage and Power (2001)). On the contrary, in Latin American markets N(Buy) exceeds N(Sell) across all rules, with clear evidence in favor of a primary upward trend in Mexico, and to a lesser extent, Brazil and Chile. This implies that it will be harder to “beat” the buy-and-hold benchmark in these countries, as is indeed the case.

The row labeled “Annualized return (%)” reports the excess return from following the trading rule signals (π_i) divided by the number of years in the sample ($14\frac{5}{12}$). It is clear that the trading strategy outperforms the buy-and-hold, prior to transaction costs, in all markets, excluding only two TRB rules in Thailand. In general, and particularly for VMA rules, the “double-or-out” scheme yields higher pre-trading cost returns in Asian markets compared to Latin American countries, as expected. Indonesia exhibits the highest return among all markets for all VMA and TRB rules. There is a discernible pattern of pre-cost profitability among VMA and TRB rules, with the “faster” rules ((1,50,0) and (1,50,0.01)) exhibiting the highest returns.

Note that borrowing and lending at the risk-free interest rate negligibly affects trading rule returns and associated t-ratios (calculated assuming a zero interest rate in Tables 3.4 and 3.5). This is so as returns reported in the Buy-Sell rows of Tables 3.4 and 3.5 are

so much larger than T-bill rates. For example, the average buy-sell return of VMA rules across all markets (i.e. the average of the sum of the VMA rule average buy-sell spreads) is equal to 0.22%; this compares with an average daily T-Bill rate of 0.02% over the sample period.

The profitability of the various trading rules depends on the frequency of trades and associated transaction costs, which can be substantial in emerging markets (see Bekaert et al. (1998)), eroding profits from trade-intensive strategies. Though actual transaction costs vary substantially among emerging markets, the mean of the estimates reported by Bekaert et al. (1998) is close to 1%. Ratner and Leal (1999) report that in Taiwan, Thailand, Argentina, and Brazil trading costs are 0.50% or less (in the two latter countries broker fees and taxes are excluded), but exceed 1% in Indonesia (1.25%), Philippines (1.50%), Mexico (1.80%), and Chile (2.00%). Of course, these are early to mid-1990s figures, and are likely to have declined in the latter half of our sample period. Van der Hart et al. (2003) use 1% one-way costs for large institutional US investors in emerging markets, but also check the sensitivity of their stock selection strategies in emerging markets to 1.5% and 2.0% costs.

We report break-even costs for the “double-or-out” strategy that quite exceed the aforementioned estimates. This contrasts with results for the US (Bessembinder and Chan (1998), Fang and Xu (2003)), and the UK (Hudson et al. (1996)), which indicate that the “double-or-out” strategy does not offer excess returns after transaction costs. VMA rules appear consistently profitable in Asian markets, with some rules allowing profits in Latin American markets as well. Particularly for the former markets, profits from the “double-or-out” strategy can reach a few percentage points per trade for a significant number of rules. This finding is relatively robust to the exclusion of the Asian crisis period from the analysis, since although the degree of profitability is reduced, it is evident that excess returns can still be obtained in all Asian markets for most rules. The higher profitability

of VMA rules in Asian countries relative to Latin American markets reflects our findings of higher predictability in the former markets.

On the contrary, TRB rules, though mostly statistically significant, do not generally allow for excess returns since, apart from break-even costs in Indonesia, have their profits eroded even by 1% transaction costs. Parisi and Vasquez (2000) also found that VMA rules outperform TRB rules in the case of Chile. The latter result is mainly because of the construction of the TRB rules, which, due to the fixed 10-day holding period, have much fewer buy and sell returns than corresponding VMA rules, and therefore the trading strategy yields lower average returns. TRB rules are also generally more trade-intensive than corresponding VMA rules (in terms of position “switches”). One can also observe that the “faster” VMA and TRB rules, being trade intensive, do not always yield higher break-even costs, even though have higher pre-cost returns (there is actually no clear pattern across individual rules regarding profitability).

As with pre-transaction cost results, Indonesia remains the most profitable market after transaction costs across VMA and TRB strategies. Note that trading rule returns in the Indonesian market for both VMA and TRB models are highly and consistently significant with both statistical evaluation methods.

Finally, it is important to consider the riskiness of the “double-or-out” strategy in relation to the volatility of the benchmark strategy. Beginning with VMA rules, we note that in all Asian markets, the average standard deviation of buy returns across rules (Table 3.8) is below the unconditional one-day stdev. (Table 3.1) by an amount almost equal to that by which average sell return volatility (Table 3.8) exceeds the unconditional stdev. With an almost equal number of buy and sell signals in Asian markets, the “double or out” strategy should not be riskier on average compared to the buy-and-hold. In Latin America, however, where the number of buy signals exceeds that of sell signals consistently, the strategy should be less risky than the buy-and-hold, particularly in Argentina and

Chile where both buy and sell signal return volatility (Table 3.8) is less than the buy-and-hold volatility (Table 3.2). Similar considerations reveal that in Indonesia, Argentina, Brazil, and Chile, the trading strategy based on TRB rules will exhibit somewhat higher volatility (see Table 3.9 for standard deviations of TRB rule returns) than the benchmark strategy.

3.7 Conclusion

In this chapter we have carried out a comprehensive study of the returns generating process and profitability of relatively simple and well known to traders technical rules in ECM, notably four Asian and four Latin American countries. Using daily data since 1988 for all countries, we have provided evidence that the dollar denominated returns generating process exhibits statistically significant long memory effects in the volatility but not in the mean. “Trading” upon such findings, we concluded that moving average and trading range break rules outperform the simple “buy-and-hold” strategy for all markets before transaction costs. Notably, though, in the four Asian countries examined, the profitability of the trading rules is sustained even after transaction costs are taken into consideration.

Suggestions of possible data snooping biases in our trading results are partially removed with the use of a data set that was previously not studied in the academic literature. Bootstrap simulations reveal that the “favorite” stochastic process for the generation of returns in ECM can reproduce technical trading rule results, particularly for Latin American countries, that are consistent with those from the actual data series.

The robustness of our results is further reinforced by: First, predictability in ECM cannot be attributed to nonsynchronous measurement biases. Second, the significant forecasting performance of our trading rules in the Asian stock markets is not driven by the negative returns outliers observed during the mid-late 1990’s Asian crisis. Third, in contrast with previous studies, break-even costs for the “double-or-out” strategy exceed

reasonable one-way trading costs. In particular, VMA rules for Asian markets lead to profits for the “double-or-out” strategy that can reach a few percentage points (annualized) per trade for a significant number of trades.

All in all, our results cast doubt on the weak form efficiency of ECM economies. In view of our results for the Asian markets, it would be interesting for future research to investigate whether a gradual transition to a developed market, “efficient-type” status, has emerged after the Asian crisis, leading to a significant decline in the predictability and profitability of trading rules. Also, whether the investment flow by foreigners in ECM significantly affects the returns generating process. The latter could be done, for instance, by including the dollar amount of net daily trades by foreigners as an independent variable in the statistical model of returns. At present, the lack of a sufficiently long data series does not allow us to carry out such tasks.

Table 3.1
Summary Statistics for Asian Market Returns

Panel A: Daily Returns				
	Philippines (PHI)	Taiwan (TAI)	Thailand (THA)	Indonesia (IND)
Mean	0.000056 (1.5%)	0.000194 (5.1%)	-0.000043 (-1.1%)	0.000048(1.3%)
Stdev	0.0176	0.0214	0.0220	0.0290
Skewness	0.7188	0.0115	0.7033	0.2030
kurtosis	12.8794	2.4060	9.1972	43.7281
Minimum	-0.1094	-0.113	-0.1444	-0.4308
Maximum	0.2197	0.1266	0.1810	0.4451
Jarque-Bera	4257[0.00]	520[0.00]	2563[0.00]	19229[0.00]
ADF Value	27.27[0.00]	-26.37[0.00]	-27.69[0.00]	-26.82[0.00]
Autocorrelation Statistics for daily returns				
$\rho(1)$	0.1831 ^b	0.0631 ^b	0.1886 ^b	0.1907 ^b
$\rho(2)$	0.0098	0.0454 ^b	0.0297	0.0661 ^b
$\rho(3)$	-0.0029	0.0430 ^b	-0.0163	-0.0231
$\rho(4)$	0.0056	-0.0183	0.0119	-0.0782 ^b
$\rho(5)$	-0.0281	0.0045	-0.0446 ^b	0.0130
$\rho(10)$	0.0282	0.0196	0.0428 ^b	0.0624 ^b
$\rho(100)$	-0.0224	0.0177	-0.0009	0.0213
Autocorrelation Statistics for daily squared returns				
$\rho(1)$	0.1657 ^b	0.1677 ^b	0.2143 ^b	0.2719 ^b
$\rho(2)$	0.0897 ^b	0.2902 ^b	0.1927 ^b	0.1278 ^b
$\rho(3)$	0.0900 ^b	0.1833 ^b	0.2627 ^b	0.1653 ^b
$\rho(4)$	0.0467 ^b	0.1983 ^b	0.0932 ^b	0.1890 ^b
$\rho(5)$	0.0689 ^b	0.1692 ^b	0.1312 ^b	0.1960 ^b
$\rho(10)$	0.0707 ^b	0.2783 ^b	0.1732 ^b	0.1072 ^b
$\rho(100)$	0.0234	0.0912 ^b	0.0509 ^b	0.0360 ^b
Bartlett Standard Error: 0.0320				
Panel B: Ten-Day Returns				
Mean	0.00056	0.0019	-0.00043	0.00048
Stdev.	0.0621	0.0746	0.0822	0.0960
Skewness	-0.2428	-0.4259	-0.0477	0.8371
Kurtosis	1.9275	1.3549	3.1908	6.8698

Note: The daily MSCI index series is from January 1 1988 through May 31, 2002. Returns are measured as log differences of the index level over the full sample. Numbers in parenthesis next to daily means are annualized returns assuming 260 trading days per year. 10-day returns are based on 10-day nonoverlapping periods. $\rho(i)$ is the estimated autocorrelation coefficient at lag i for each series. Coefficients marked with ^b indicate significant autocorrelations at the 5% level. The Bartlett standard error is calculated as $1.96/\sqrt{T}$, where T is the sample length, and is an approximate guide to the significance of autocorrelations statistics.

Table 3.2
Summary Statistics for Latin American Market Returns

Panel A: Daily Returns				
	Mexico (MEX)	Brazil (BRA)	Argentina (ARG)	Chile (CHI)
Mean	0.000766 (20.0%)	0.000463 (12.0%)	0.000305 (8.0%)	0.000439 (11.4%)
Stdev	0.0198	0.0289	0.0410	0.0128
Skewness	-0.0759	-0.4592	-2.8740	-0.5036
kurtosis	12.6393	7.9084	90.1098	11.6083
Minimum	-0.2176	-0.2635	-0.9270	-0.1623
Maximum	0.1784	0.2123	0.4559	0.0870
Jarque-Bera	5038[0.00]	2514[0.00]	24327[0.00]	4124[0.00]
ADF Value	-26.30[0.00]	-25.36[0.00]	-29.54[0.00]	-25.12[0.00]
Autocorrelation Statistics for daily returns				
$\rho(1)$	0.1288 ^b	0.1473 ^b	-0.0309	0.2287 ^b
$\rho(2)$	-0.0160	0.0563 ^b	-0.1461 ^b	0.0390 ^b
$\rho(3)$	0.0086	0.0316	0.0697 ^b	-0.0135
$\rho(4)$	0.0153	0.0159	-0.0094	0.0121
$\rho(5)$	0.0107	0.0147	-0.0493 ^b	0.0355 ^b
$\rho(10)$	0.0455 ^b	0.0097	0.0210	0.0435 ^b
$\rho(100)$	0.0157	0.0293	0.0113	0.0094
Autocorrelation Statistics for daily squared returns				
$\rho(1)$	0.2591 ^b	0.2722 ^b	0.0773 ^b	0.1045 ^b
$\rho(2)$	0.1375 ^b	0.2310 ^b	0.1907 ^b	0.0748 ^b
$\rho(3)$	0.1365 ^b	0.1965 ^b	0.0235 ^b	0.1022 ^b
$\rho(4)$	0.0922 ^b	0.0949 ^b	0.0556 ^b	0.0391 ^b
$\rho(5)$	0.1142 ^b	0.0846 ^b	0.0897 ^b	0.0459 ^b
$\rho(10)$	0.0991 ^b	0.1678 ^b	0.0991 ^b	0.0385 ^b
$\rho(100)$	-0.0044	0.0234	0.0065	-0.0059
Bartlett standard error = 0.0320				
Panel B: Ten-Day Returns				
Mean	0.00766	0.00463	0.00305	0.00439
Stdev.	0.0686	0.1083	0.1130	0.0510
Skewness	-0.4269	-1.4365	0.985	-0.1428
Kurtosis	3.3692	9.7238	5.8639	1.1649

Note: The daily MSCI index series is from January 1 1988 through May 31, 2002. Returns are measured as log differences of the index level over the full sample. Numbers in parenthesis next to daily means are annualized returns assuming 260 trading days per year. 10-day returns are based on 10-day nonoverlapping periods. $\rho(i)$ is the estimated autocorrelation coefficient at lag i for each series. Coefficients marked with ^b indicate significant autocorrelations at the 5% level. The Bartlett standard error is calculated as $1.96/\sqrt{T}$, where T is the sample length, and is an approximate guide to the significance of autocorrelations statistics.

Table 3.3

Econometric Models for Asian and Latin American Market Daily Returns

	PHI	TAI	THA	IND	MEX	BRA	ARG	CHI
μ	0.0538 ^c (0.030)	0.0704 ^c (0.039)	0.0373 (0.030)	0.0348 (0.030)	0.1532 ^a (0.020)	0.1039 ^a (0.039)	0.0778 ^b (0.036)	0.0128 (0.013)
ρ_1	0.1805 ^a (0.018)	0.0477 ^a (0.018)	0.1551 ^a (0.019)	0.2004 ^a (0.021)	0.1789 ^a (0.018)	0.1454 ^a (0.018)	0.0939 ^a (0.017)	0.2759 ^a (0.018)
ρ_2		0.0414 ^a (0.018)	0.0541 ^b (0.018)	0.0433 ^b (0.023)			-0.0474 ^a (0.018)	-0.0547 ^a (0.018)
ρ_3		0.0339 ^b (0.015)					0.0395 ^b (0.019)	
ω	0.1468 ^a (0.026)	0.3474 ^a (0.059)	0.2085 ^a (0.038)	0.1491 ^a (0.025)	0.3286 ^a (0.048)	0.1522 ^a (0.045)	0.1422 ^a (0.026)	0.1355 ^a (0.019)
β	0.5518 ^a (0.061)	0.2721 ^a (0.037)	0.2027 ^a (0.036)	0.1785 ^a (0.036)	0.1313 ^a (0.046)	0.6008 ^a (0.061)	0.7461 ^a (0.035)	0.2495 ^a (0.046)
ϕ	0.1390 ^a (0.047)					0.1514 ^a (0.037)	0.1138 ^a (0.035)	
δ	0.5244 ^a (0.073)	0.3231 ^a (0.059)	0.3614 ^a (0.031)	0.4912 ^a (0.029)	0.3563 ^a (0.040)	0.5538 ^a (0.064)	0.7677 ^a (0.050)	0.4340 ^a (0.044)
$\ln(L)$	-6954	-7791	-7459	-7209	-7250	-8753	-8988	-5801
Skewness	1.27	-0.03	0.13	0.57	-0.42	-0.58	-0.26	-0.39
Kurtosis	25.87	4.67	6.76	12.17	6.53	7.04	6.72	10.61
$Q(50)$	52.36	62.54	63.35	64.01	58.53	61.76	56.73	63.36
$Q^2(50)$	5.16	64.21	53.04	19.32	37.37	39.68	41.10	61.50
BDS	1.55	-0.61	1.68 ^c	1.88 ^c	-0.71	0.97	0.21	-0.17

Note: Results are for returns $\times 100$. Only parsimonious specifications of model (3.13) are presented for each market. QMLE asymptotic standard errors are in parentheses below corresponding parameter estimates. ^a, ^b, and ^c denote significance at the 1, 5, and 10 percent levels respectively. The quantity $\ln(L)$ is the value of the maximized log likelihood. Skewness and Kurtosis refer to the standardized residuals. The $Q(50)$ and $Q^2(50)$ statistics are the Ljung-Box test statistics for 50 degrees of freedom to test for serial correlation in the standardized and squared standardized residuals respectively. In all cases the Ljung-Box statistics are insignificant at the 5% level. We also report the BDS test statistic for standardized residuals with embedding dimension m equal to five and ϵ equal to one standard deviation.

Table 3.4
Results for Technical Trading Rules in Asian Markets

	PHI		TAI		THA		IND	
	VMA	TRB	VMA	TRB	VMA	TRB	VMA	TRB
(1, 50, 0)								
Buy	0.0019 ^a	0.0208 ^a	0.0019 ^a	0.0183 ^b	0.0021 ^a	0.0137	0.0029 ^a	0.0329 ^a
Sell	-0.0020 ^a	-0.0147 ^b	-0.0018 ^a	-0.0138 ^b	-0.0024 ^a	-0.0107	-0.0024 ^a	-0.0192 ^c
Buy-Sell	0.0039 ^a	0.0355 ^a	0.0037 ^a	0.0321 ^a	0.0045 ^a	0.0244 ^c	0.0053 ^a	0.0520 ^a
(1, 50, 0.01)								
Buy	0.0023 ^a	0.0243 ^a	0.0023 ^a	0.0241 ^a	0.0023 ^a	0.0109	0.0027 ^a	0.0433 ^a
Sell	-0.0021 ^a	-0.0164 ^b	-0.0019 ^a	-0.0103	-0.0026 ^a	-0.0045	-0.0032 ^a	-0.0218 ^c
Buy-Sell	0.0044 ^a	0.0407 ^a	0.0042 ^a	0.0343 ^a	0.0049 ^a	0.0154	0.0059 ^a	0.0650 ^a
(1, 150, 0)								
Buy	0.0010 ^c	0.0147	0.0011	0.0120	0.0008	0.0113	0.0009	0.0469 ^a
Sell	-0.0014 ^a	-0.0149	-0.0012 ^b	-0.0322 ^a	-0.0011 ^c	0.0008	-0.0020 ^a	-0.0208
Buy-Sell	0.0023 ^a	0.0296 ^b	0.0022 ^a	0.0442 ^a	0.0019 ^a	0.0106	0.0029 ^a	0.0677 ^a
(1, 150, 0.01)								
Buy	0.0009 ^c	0.0146	0.0011	0.0223 ^c	0.0008	0.0111	0.0010	0.0723 ^a
Sell	-0.0014 ^a	-0.0053	-0.0012 ^b	-0.0249 ^b	-0.0012 ^c	0.0210	-0.0021 ^a	-0.0253
Buy-Sell	0.0023 ^a	0.0199	0.0023 ^a	0.0472 ^a	0.0020 ^a	-0.0099	0.0031 ^a	0.0976 ^a
(5, 150, 0)								
Buy	0.0008		0.0009		0.0004		0.0008	
Sell	-0.0011 ^b		-0.0092 ^c		-0.0008		-0.0017 ^b	
Buy-Sell	0.0020 ^a		0.0019 ^a		0.0012		0.0025 ^a	
(5, 150, 0.01)								
Buy	0.0008		0.0010		0.0004		0.0009	
Sell	-0.0011 ^b		-0.0009 ^c		-0.0009		-0.0015 ^c	
Buy-Sell	0.0019 ^a		0.0019 ^a		0.0014 ^c		0.0023	
(1, 200, 0)								
Buy	0.0006	0.0166 ^c	0.0009	0.0020	0.0006	0.0158	0.0012	0.0494 ^a
Sell	-0.0012 ^a	-0.0182 ^c	-0.0011 ^b	-0.0383 ^a	-0.0011	-0.0024	-0.0019 ^a	-0.0194
Buy-Sell	0.0018 ^a	0.0347 ^a	0.0020 ^a	0.0403 ^b	0.0017 ^b	0.0182	0.0032 ^a	0.0688 ^a
(1, 200, 0.01)								
Buy	0.0007	0.0274 ^a	0.0009	0.0073	0.0007	0.0176	0.0012	0.0692 ^a
Sell	-0.0013 ^a	-0.0065	-0.0011 ^b	-0.0255 ^b	-0.0012 ^c	0.0194	-0.0020 ^a	-0.0202
Buy-Sell	0.0020 ^a	0.0339 ^b	0.0020 ^a	0.0329 ^c	0.0018 ^a	-0.0018	0.0032 ^a	0.0894 ^a
Average	0.0026	0.0324	0.0025	0.0385	0.0024	0.0095	0.0035	0.0734
Buy-and-hold	5.6*10 ⁻⁵	5.6*10 ⁻⁴	1.94*10 ⁻³	1.94*10 ⁻²	-4.3*10 ⁻⁵	-4.3*10 ⁻⁴	4.8*10 ⁻⁵	4.8*10 ⁻⁴

Note: VMA refers to Variable-Length-Moving-Average Rules, and TRB to Trading-Range-Break Rules. Rules are defined as (S, L, B), where S is the length of the short moving average (does not represent anything in the case of TRB rules), L is the length of the long moving average (represents the number of days over which maximum and minimum prices are calculated in the case of TRB rules), and B is the percentage band. Buy, sell, and buy-sell returns are averages from following the trading rule signals with a one-day lag over the whole sample period. ^a, ^b, and ^c denote significance of the mean buy and sell return relative to the unconditional daily mean (10-day mean for TRB rules), and mean buy-sell return relative to zero, at the 1, 5, and 10 percent levels respectively. The row labeled Average reports the simple average of the buy-sell spread across all rules. The average daily (and 10-day) returns to following a buy-and-hold strategy (equivalent to the unconditional mean returns for each stock index from Table 3.1) are provided for ease of comparison.

Table 3.5
Results for Technical Trading Rules in Latin American Markets

	MEX		BRA		ARG		CHI	
	VMA	TRB	VMA	TRB	VMA	TRB	VMA	TRB
(1,50,0)								
Buy	0.0019 ^b	0.0163	0.0023 ^b	0.0092	0.0022	0.0040	0.0017 ^a	0.0133
Sell	-0.0009 ^a	-0.0032	-0.0019 ^a	-0.0228 ^c	-0.0026	-0.0211	-0.0010 ^a	-0.0047
Buy-Sell	0.0029 ^a	0.0196 ^c	0.0043	0.0319 ^c	0.0048	0.0251	0.0028 ^a	0.0180 ^b
(1,50,0.01)								
Buy	0.0022 ^a	0.0161	0.0023 ^b	0.0112	0.0022	-0.0019	0.0020 ^a	0.0122
Sell	-0.0013 ^a	-0.0013	-0.0020 ^a	-0.0199	-0.0017	-0.0038	-0.0012 ^a	-0.0056
Buy-Sell	0.0035 ^a	0.0174	0.0043 ^a	0.0311	0.0040 ^a	0.0018	0.0033 ^a	0.0178 ^c
(1,150,0)								
Buy	0.0012	0.0130	0.0012	0.0051	0.0001	0.0242	0.0010	0.0147
Sell	-0.0002	-0.0263 ^b	-0.0095	-0.0086	-0.0005	0.0160	-0.0003 ^b	-0.0079
Buy-Sell	0.0014 ^c	0.0394 ^a	0.0017	0.0137	0.0006	0.0081	0.0013	0.0227 ^b
(1,150,0.01)								
Buy	0.0012	0.0148	0.0012	0.0054	0.0003	0.0198	0.0011 ^c	0.0151
Sell	-0.0003	-0.0395 ^a	-0.0007	-0.0120	-0.0022	0.0145	-0.0003 ^c	-0.0105
Buy-Sell	0.0015 ^b	0.0543 ^a	0.0019	0.0173	0.0006	0.0053	0.0014 ^a	0.0257 ^c
(5,150,0)								
Buy	0.0010		0.0004		-0.0001		0.0008	
Sell	0.0002		-0.0002		-0.0002		-0.0001	
Buy-Sell	0.0007		0.0006		0.0001		0.0009 ^b	
(5,150,0.01)								
Buy	0.0011		0.0005		0.0001		0.0008	
Sell	0.0001		-0.0002		-0.0002		0.0000	
Buy-Sell	0.0010		0.0007		0.0003		0.0009	
(1,200,0)								
Buy	0.0010	0.0115	0.0008	0.0110	0.0009	0.0229	0.0010	0.0163
Sell	0.0001	-0.0361 ^b	-0.0003	-0.0039	-0.0007	0.0164	-0.0002 ^c	-0.0061
Buy-Sell	0.0008	0.0476 ^b	0.0010	0.0149	0.0016	0.0065	0.0012 ^a	0.0224
(1,200,0.01)								
Buy	0.0009	0.0151	0.0007	0.0141	0.0004	0.0310	0.0010 ^c	0.0179
Sell	0.0001	-0.0361 ^b	0.0001	-0.0013	-0.0008	0.0148	-0.0002	-0.0300 ^a
Buy-Sell	0.0008	0.0513 ^a	0.0006	0.0155	0.0017	0.0162	0.0013 ^a	0.0479 ^a
Average	0.0016	0.0383	0.0019	0.0207	0.0016	0.0105	0.0016	0.0257
Buy-and-hold	7.7*10 ⁻⁴	7.7*10 ⁻³	4.6*10 ⁻⁴	4.6*10 ⁻³	3.0*10 ⁻⁴	3.0*10 ⁻³	4.4*10 ⁻⁴	4.4*10 ⁻³

Note: VMA refers to Variable-Length-Moving-Average Rules, and TRB to Trading-Range-Break Rules. Rules are defined as (S, L, B), where S is the length of the short moving average (does not represent anything in the case of TRB rules), L is the length of the long moving average (represents the number of days over which maximum and minimum prices are calculated in the case of TRB rules), and B is the percentage band. Buy, sell, and buy-sell returns are averages from following the trading rule signals with a one-day lag over the whole sample period. ^a, ^b, and ^c denote significance of the mean buy and sell return relative to the unconditional daily mean (10-day mean for TRB rules), and mean buy-sell return relative to zero, at the 1, 5, and 10 percent levels respectively. The row labeled Average reports the simple average of the buy-sell spread across all rules. The average daily (and 10-day) returns to following a buy-and-hold strategy (equivalent to the unconditional mean returns for each stock index from Table 3.1) are provided for ease of comparison.

Table 3.6

Simulation Tests from Model Bootstraps for Individual VMA Rules

	PHI	TAI	THA	IND	MEX	BRA	ARG	CHI
(1, 50, 0)								
Buy	0.092	0.042	0.042	0.058	0.332	0.236	0.118	0.054
Buy stdev	0.746	0.380	0.340	0.266	0.814	0.574	0.324	0.730
Sell	0.912	0.960	0.946	0.896	0.824	0.744	0.176	0.866
Sell stdev	0.406	0.086	0.142	0.112	0.150	0.448	0.304	0.860
Buy-Sell	0.060	0.032	0.024	0.058	0.176	0.204	0.236	0.048
(1, 50, 0.01)								
Buy	0.058	0.012	0.038	0.096	0.196	0.306	0.148	0.052
Buy stdev	0.760	0.358	0.336	0.270	0.814	0.566	0.314	0.170
Sell	0.890	0.956	0.950	0.940	0.876	0.716	0.176	0.888
Sell stdev	0.396	0.076	0.146	0.114	0.146	0.444	0.306	0.654
Buy-Sell	0.056	0.018	0.026	0.050	0.114	0.246	0.254	0.038
(1, 150, 0)								
Buy	0.232	0.150	0.182	0.214	0.702	0.572	0.416	0.140
Buy stdev	0.902	0.420	0.528	0.512	0.838	0.574	0.212	0.718
Sell	0.916	0.930	0.742	0.924	0.694	0.494	0.130	0.632
Sell stdev	0.326	0.104	0.116	0.098	0.140	0.472	0.310	0.680
Buy-Sell	0.092	0.046	0.170	0.092	0.384	0.518	0.454	0.194
(1, 150, 0.01)								
Buy	0.274	0.224	0.200	0.214	0.618	0.562	0.366	0.130
Buy stdev	0.894	0.404	0.586	0.502	0.850	0.566	0.216	0.750
Sell	0.912	0.940	0.752	0.928	0.708	0.342	0.082	0.548
Sell stdev	0.320	0.098	0.112	0.098	0.128	0.468	0.298	0.646
Buy-Sell	0.104	0.058	0.172	0.088	0.346	0.462	0.456	0.238
(5, 150, 0)								
Buy	0.148	0.100	0.184	0.140	0.596	0.722	0.316	0.114
Buy stdev	0.908	0.470	0.482	0.538	0.644	0.592	0.222	0.740
Sell	0.950	0.956	0.708	0.954	0.702	0.634	0.170	0.676
Sell stdev	0.346	0.118	0.130	0.108	0.156	0.466	0.282	0.690
Buy-Sell	0.056	0.014	0.148	0.034	0.356	0.464	0.364	0.148
(5, 150, 0.01)								
Buy	0.172	0.068	0.180	0.130	0.508	0.674	0.264	0.126
Buy stdev	0.914	0.456	0.506	0.516	0.648	0.592	0.240	0.722
Sell	0.924	0.928	0.814	0.926	0.744	0.622	0.160	0.540
Sell stdev	0.354	0.098	0.120	0.108	0.176	0.472	0.286	0.696
Buy-Sell	0.068	0.018	0.114	0.050	0.278	0.480	0.354	0.224
(1, 200, 0)								
Buy	0.496	0.244	0.234	0.106	0.812	0.776	0.212	0.132
Buy stdev	0.928	0.520	0.564	0.462	0.748	0.572	0.188	0.760
Sell	0.904	0.938	0.766	0.946	0.550	0.474	0.188	0.574
Sell stdev	0.314	0.036	0.112	0.108	0.134	0.498	0.294	0.672
Buy-Sell	0.140	0.054	0.178	0.052	0.610	0.656	0.296	0.206
(1, 200, 0.01)								
Buy	0.416	0.260	0.252	0.114	0.858	0.794	0.226	0.120
Buy stdev	0.908	0.500	0.570	0.448	0.722	0.558	0.190	0.744
Sell	0.906	0.922	0.816	0.095	0.562	0.326	0.180	0.528
Sell stdev	0.314	0.094	0.104	0.104	0.120	0.524	0.214	0.656
Buy-Sell	0.140	0.066	0.176	0.060	0.616	0.800	0.286	0.326

Note: Returns series are simulated (and exponentiated into a price series) using the estimated parameters and standardized residuals for the chosen econometric specification for each market as per Table 3.3. The trading rules are applied to each simulated series. Entries report the fraction of outcomes in 500 simulations of the returns generating process where the buy returns, sell returns, standard deviations of buy and sell returns, and the buy-sell differential, is larger than that observed in the actual data.

Table 3.7
Simulation Tests from Model Bootstraps for Individual TRB Rules

	PHI	TAI	THA	IND	MEX	BRA	ARG	CHI
(1,50,0)								
Buy	0.032	0.022	0.063	0.022	0.186	0.390	0.364	0.066
Buy stdev	0.754	0.418	0.774	0.342	0.896	0.496	0.410	0.630
Sell	0.922	0.960	0.881	0.920	0.794	0.920	0.754	0.832
Sell stdev	0.558	0.302	0.110	0.350	0.230	0.226	0.866	0.666
Buy-Sell	0.020	0.010	0.063	0.014	0.132	0.076	0.194	0.046
(1,50,0.01)								
Buy	0.040	0.010	0.182	0.024	0.206	0.302	0.422	0.148
Buy stdev	0.854	0.482	0.880	0.176	0.990	0.466	0.362	0.740
Sell	0.892	0.818	0.338	0.854	0.688	0.876	0.480	0.790
Sell stdev	0.556	0.258	0.306	0.372	0.314	0.250	0.862	0.864
Buy-Sell	0.026	0.022	0.292	0.016	0.188	0.094	0.550	0.100
(1,150,0)								
Buy	0.102	0.218	0.186	0.040	0.384	0.552	0.178	0.086
Buy stdev	0.668	0.422	0.900	0.432	0.734	0.572	0.502	0.480
Sell	0.906	0.996	0.266	0.886	0.924	0.676	0.214	0.830
Sell stdev	0.520	0.170	0.126	0.250	0.186	0.458	0.600	0.414
Buy-Sell	0.060	0.006	0.362	0.026	0.078	0.352	0.450	0.078
(1,150,0.01)								
Buy	0.198	0.050	0.246	0.022	0.274	0.514	0.094	0.132
Buy stdev	0.884	0.484	0.922	0.134	0.940	0.472	0.234	0.610
Sell	0.640	0.948	0.032	0.840	0.948	0.684	0.126	0.798
Sell stdev	0.480	0.140	0.282	0.264	0.144	0.556	0.450	0.458
Buy-Sell	0.198	0.018	0.782	0.012	0.052	0.342	0.244	0.112
(1,200,0)								
Buy	0.144	0.578	0.128	0.042	0.444	0.354	0.150	0.070
Buy std	0.684	0.762	0.936	0.562	0.652	0.406	0.566	0.602
Sell	0.874	0.996	0.378	0.824	0.942	0.616	0.232	0.748
Sell std.	0.582	0.160	0.150	0.224	0.092	0.534	0.718	0.260
Buy-Sell	0.082	0.024	0.220	0.044	0.062	0.364	0.479	0.090
(1,200,0.01)								
Buy	0.082	0.390	0.184	0.034	0.264	0.254	0.110	0.110
Buy stdev	0.894	0.790	0.906	0.138	0.942	0.500	0.526	0.760
Sell	0.652	0.930	0.042	0.740	0.916	0.556	0.264	0.902
Sell stdev	0.440	0.130	0.318	0.234	0.074	0.570	0.700	0.310
Buy-Sell	0.126	0.090	0.594	0.034	0.066	0.358	0.382	0.028

Note: Returns series are simulated (and exponentiated into a price series) using the estimated parameters and standardized residuals for the chosen econometric specification for each market as per Table 3.3. Entries report the fraction of outcomes in 500 simulations of the returns generating process where the buy returns, sell returns, standard deviations of buy and sell returns, and the buy-sell differential, is larger than that observed in the actual data.

Table 3.8
Simulation Tests from Model Bootstraps, VMA Rule Averages

	Buy	Buy stdev	Sell	Sell stdev	Buy-Sell
Actual PHI Mean	0.0011	0.0141	-0.0015	0.0208	0.0026
Simulation Mean	0.0007	0.0224	-0.0006	0.0215	0.0013
fraction>PHI	0.174	0.876	0.922	0.338	0.062
Actual TAI Mean	0.0013	0.0188	-0.0012	0.0241	0.0025
Simulation Mean	0.0008	0.0191	-0.0005	0.0195	0.0013
fraction>TAI	0.090	0.438	0.940	0.082	0.028
Actual THA Mean	0.0010	0.0186	-0.0014	0.0258	0.0024
Simulation Mean	0.0005	0.0204	-0.0009	0.0195	0.0013
fraction>THA	0.116	0.476	0.860	0.122	0.072
Actual IND Mean	0.0014	0.0206	-0.0021	0.0353	0.0035
Simulation Mean	0.0006	0.0247	-0.0009	0.0234	0.0011
fraction>IND	0.092	0.424	0.936	0.102	0.052
Actual MEX Mean	0.0013	0.0150	-0.0003	0.0259	0.0016
Simulation Mean	0.0014	0.0178	9.84×10^{-5}	0.0213	0.0013
fraction>MEX	0.580	0.780	0.730	0.130	0.300
Actual BRA Mean	0.0012	0.0249	-0.0007	0.0335	0.0019
Simulation Mean	0.0017	0.0344	-0.0012	0.0444	0.0029
fraction>BRA	0.630	0.574	0.576	0.470	0.454
Actual ARG Mean	0.0008	0.0378	-0.0007	0.0393	0.0016
Simulation Mean	0.0008	0.0485	-0.0018	0.0573	0.0026
fraction>ARG	0.462	0.462	0.300	0.566	0.654
Actual CHI Mean	0.0012	0.0121	-0.0004	0.0128	0.0016
Simulation Mean	0.0007	0.0155	-0.0002	0.0166	0.0009
fraction>CHI	0.090	0.740	0.692	0.668	0.108

Note: The table presents results for the averages across all the VMA rules for each reported trading rule statistic. The actual and simulated mean return and mean standard deviation across all rules is reported, together with the fraction of simulations generating a statistic (simulated average across rules) bigger than that (the rules average) of the original series in each market.

Table 3.9
Simulation Tests from Model Bootstraps, TRB Rule Averages

	Buy	Buy stdev	Sell	Sell stdev	Buy-Sell
Actual PHI Mean	0.0197	0.0567	-0.0127	0.0743	0.0324
Simulation Mean	0.0014	0.0937	-0.0000	0.0922	0.0014
fraction>PHI	0.068	0.812	0.834	0.506	0.066
Actual TAI Mean	0.0143	0.0658	-0.0242	0.0868	0.0385
Simulation Mean	0.0040	0.0710	-0.0009	0.0737	0.0049
fraction>TAI	0.124	0.560	0.984	0.168	0.008
Actual THA Mean	0.0134	0.0540	0.0039	0.0986	0.0095
Simulation Mean	-0.0017	0.0927	-0.0068	0.0837	0.0050
fraction>THA	0.168	0.916	0.150	0.202	0.402
Actual IND Mean	0.0523	0.1508	-0.0211	0.1222	0.0734
Simulation Mean	-0.0003	0.1286	-0.0048	0.1157	0.0045
fraction>IND	0.026	0.222	0.870	0.258	0.018
Actual MEX Mean	0.0145	0.0534	-0.0238	0.1275	0.0383
Simulation Mean	0.0100	0.0705	0.0070	0.0931	0.0030
fraction>MEX	0.256	0.940	0.944	0.118	0.032
Actual BRA Mean	0.0093	0.0998	-0.0114	0.1499	0.0207
Simulation Mean	0.0043	0.1183	-0.0001	0.1770	0.0045
fraction>BRA	0.362	0.498	0.714	0.396	0.264
Actual ARG Mean	0.0166	0.1454	0.0061	0.1247	0.0105
Simulation Mean	-0.0070	0.1922	-0.0099	0.2323	0.0029
fraction>ARG	0.128	0.518	0.292	0.832	0.384
Actual CHI Mean	0.0149	0.0547	-0.0108	0.0678	0.0257
Simulation Mean	0.0019	0.0700	0.0037	0.0756	-0.0017
fraction>CHI	0.076	0.660	0.888	0.440	0.048

Note: The table presents results for the averages across all the TRB rules for each reported trading rule statistic. The actual and simulated mean return and mean standard deviation across all rules are reported, together with the fraction of simulations generating a statistic (simulated average across rules) bigger than that (the rules average) of the original series in each market.

Table 3.10

Results for VMA Rules in Asian Markets Excluding the Asian Crisis Period

	PHI	TAI	THA	IND
(1, 50, 0)				
Buy	0.0019 ^a	0.0019 ^{a*}	0.0021 ^a	0.0031 ^a
Sell	-0.0015 ^a	-0.0017 ^a	-0.0018 ^a	-0.0016 ^c
Buy-Sell	0.0034 ^a	0.0037 ^a	0.0039 ^a	0.0047 ^a
(1, 50, 0.01)				
Buy	0.0023 ^a	0.0023 ^a	0.0023 ^a	0.0032 ^a
Sell	-0.0015 ^a	-0.0018 ^a	-0.0020 ^a	-0.0020 ^a
Buy-Sell	0.0038 ^a	0.0041 ^a	0.0043 ^a	0.0052 ^a
(1, 150, 0)				
Buy	0.0011 ^c	0.0012	0.0008	0.0009
Sell	-0.0007	-0.0010 ^c	-0.0006	-0.0005
Buy-Sell	0.0018 ^a	0.0022 ^a	0.0014 ^c	0.0014
(1, 150, 0.01)				
Buy	0.0011 ^c	0.0011	0.0009	0.0010
Sell	-0.0007	-0.0011 ^b	-0.0006	-0.0005
Buy-Sell	0.0018 ^a	0.0023 ^a	0.0015 ^c	0.0015
(5,150,0)				
Buy	0.0009 ^c	0.0010	0.0005	0.0008
Sell	-0.0005	-0.0009	-0.0002	-0.0002
Buy-Sell	0.0014 ^a	0.0019 ^a	0.0007	0.0010
(5, 150, 0.01)				
Buy	0.0009	0.0011	0.0006	0.0009
Sell	-0.0004	-0.0008	-0.0003	0.0002
Buy-Sell	0.0013 ^a	0.0019 ^a	0.0009	0.0007
(1, 200, 0)				
Buy	0.0006	0.0009	0.0006	0.0012
Sell	-0.0006	-0.0010 ^c	-0.0011	-0.0009
Buy-Sell	0.0012 ^c	0.0019 ^a	0.0017 ^b	0.0021 ^c
(1, 200, 0.01)				
Buy	0.0006	0.0009	0.0007	0.0012
Sell	-0.0006	-0.0009 ^c	-0.0012 ^c	-0.0009
Buy-Sell	0.0012 ^c	0.0019 ^a	0.0018 ^a	0.0021 ^c
Average	0.0020	0.0025	0.0019	0.0023

Note: Buy, sell, and buy-sell returns are defined in Tables 3.4 and 3.5. The last row is the average buy-sell spread across the 8 VMA rules. The periods excluded from the analysis are: 2 July 1997 to 30 September 1998 for Thailand, 11 July 1997 to 30 September 1998 for Philippines, 4 August 1997 to 6 October 1998 for Indonesia, and 17 October 1997 to 30 September 1998 for Taiwan.

Table 3.11
“Double-or-Out” VMA Rule Strategy Returns and Break-Even Costs

	PHI	TAI	THA	IND	MEX	BRA	ARG	CHI
(1, 50, 0)								
N(Trading)	134 (129)	137 (129)	114 (101)	100 (88)	155	173	156	137
N(Buy)	1834 (1708)	1653 (1546)	1686 (1572)	1810 (1713)	2189	1873	1851	1878
N(Sell)	1722 (1408)	1772 (1522)	1799 (1504)	1711 (1432)	1359	1598	1697	1686
Annualized return (%)	47.7 (37.1)	44.1 (39.0)	54.3 (41.7)	64.0 (51.9)	36.9	51.6	46.6	34.5
Break-even cost (%)	2.56 (2.07)	2.32 (2.18)	3.44 (2.98)	4.61 (4.25)	1.71	2.15	2.15	1.81
(1, 50, 0.01)								
N(Trading)	127 (121)	150 (143)	127 (123)	105 (91)	148	168	172	126
N(Buy)	1636 (1523)	1483 (1514)	1514 (1398)	1657 (1560)	2002	1709	1711	1670
N(Sell)	1523 (1218)	1559 (1356)	1657 (1365)	1775 (1302)	1193	1430	1430	1450
Annualized return (%)	47.8 (37.3)	44.1 (41.4)	54.5 (41.1)	71.1 (52.7)	40.3	46.6	43.1	35.6
Break-even cost (%)	2.72 (2.22)	2.12 (2.09)	3.09 (2.41)	4.88 (4.17)	1.96	2.00	1.81	2.04
(1,150,0)								
N(Trading)	43 (39)	67 (61)	89 (84)	62 (62)	89	68	111	73
N(Buy)	1629 (1547)	1758 (1714)	1702 (1645)	1339 (1312)	2275	1983	1788	1969
N(Sell)	1581 (1303)	1724 (1472)	1757 (1416)	1684 (1350)	1129	1581	1635	1514
Annualized return (%)	26.3 (18.4)	27.1 (24.5)	23.6 (15.4)	31.9 (12.77)	18.3	21.4	6.3	16.5
Break-even cost (%)	4.41 (3.41)	2.92 (2.90)	1.91 (1.32)	3.71 (1.48)	1.48	2.27	0.41	1.63
(1, 150, 0.01)								
N(Trading)	51 (48)	74 (68)	82 (78)	56 (56)	81	75	110	78
N(Buy)	1550 (1473)	1680 (1638)	1586 (1536)	1254 (1226)	2196	1919	1707	1841
N(Sell)	1511 (1242)	1631 (1382)	1654 (1322)	1616 (1290)	1052	1467	1538	1361
Annualized return (%)	25.2 (16.8)	26.5 (23.6)	22.8 (15.4)	32.7 (13.22)	19.3	22.9	6.0	15.7
Break-even cost (%)	3.56 (2.53)	2.58 (2.50)	2.01 (1.43)	4.21 (1.70)	1.71	2.20	0.39	1.45
(5, 150, 0)								
N(Trading)	33 (31)	44 (38)	58 (54)	40 (40)	54	48	69	47
N(Buy)	1638 (1558)	1738 (1694)	1712 (1664)	1346 (1327)	2260	2001	1825	1791
N(Sell)	1580 (1304)	1733 (1496)	1776 (1448)	1698 (1372)	1146	1531	1637	1521
Annualized return (%)	22.2 (14.4)	22.5 (20.9)	14.7 (8.1)	28.4 (9.0)	11.3	7.8	1.1	10.7
Break-even cost (%)	4.86 (3.35)	3.69 (3.96)	1.83 (1.08)	5.11 (1.62)	1.51	1.17	0.12	1.65
(5, 150, 0.01)								
N(Trading)	30 (28)	43 (40)	58 (55)	36 (36)	50	53	67	53
N(Buy)	1567 (1493)	1662 (1631)	1592 (1544)	1258 (1241)	2199	1936	1745	1663
N(Sell)	1520 (1249)	1648 (1415)	1660 (1335)	1611 (1287)	1072	1481	1567	1381
Annualized return (%)	21.0 (13.1)	22.1 (20.0)	16.0 (9.3)	24.7 (5.47)	14.1	8.0	2.9	20.0
Break-even cost (%)	5.46 (3.37)	3.71 (3.60)	1.98 (1.22)	4.96 (1.10)	2.03	1.09	0.32	1.14
(1, 200, 0)								
N(Trading)	56 (53)	56 (56)	84 (84)	44 (44)	96	86	93	75
N(Buy)	1635 (1606)	1760 (1734)	1795 (1755)	1291 (1269)	2351	1955	1740	2043
N(Sell)	1561 (1219)	1695 (1421)	1664 (1301)	1735 (1409)	1014	1483	1659	1438
Annualized return (%)	20.7 (11.8)	24.0 (20.5)	20.7 (11.2)	35.1 (19.1)	12.7	12.5	18.9	15.0
Break-even cost (%)	2.66 (1.60)	3.09 (2.64)	1.77 (0.97)	5.75 (3.13)	0.96	1.05	1.47	1.44
(1, 200, 0.01)								
N(Trading)	59 (54)	48 (48)	77 (77)	44 (44)	94	83	79	65
N(Buy)	1548 (1353)	1697 (1673)	1685 (1650)	1192 (1171)	2243	1894	1687	1928
N(Sell)	1491 (1326)	1632 (1361)	1552 (1197)	1658 (1331)	920	1407	1578	1313
Annualized return (%)	21.2 (11.1)	23.0 (19.6)	20.6 (11.3)	33.6 (17.6)	11.6	7.7	19.3	14.7
Break-even cost (%)	2.59 (1.48)	3.45 (2.94)	1.93 (1.06)	5.51 (2.89)	0.89	0.67	1.76	1.63

Note: N(Buy) and N(Sell) are the number of buy and sell signals generated by each rule. N(trading) is the number of trades required to shift a position from “double” to “out” or vice versa. The annualized return for each rule is the annualized buy-sell spread from the “double-or-out” strategy in excess of interest rates and the buy-and-hold return. One-way break-even costs are computed as the differential between buy and sell means divided by twice the number of trades. Numbers in parenthesis represent the corresponding statistics for Asian markets excluding the Asian crisis period.

Table 3.12
 “Double-or-Out” TRB Rule Strategy Returns and Break-Even Costs

	PHI	TAI	THA	IND	MEX	BRA	ARG	CHI
(1,50,0)								
N(Trading)	157	160	154	166	164	147	149	162
N(Buy)	81	83	80	85	108	93	90	88
N(Sell)	76	77	74	81	56	54	59	74
Annualized return (%)	19.4	17.9	13.1	30.2	13.5	14.4	11.1	10.5
Break-even cost (%)	0.89	0.81	0.61	1.31	0.59	0.71	0.54	0.47
(1,50,0.01)								
N(Trading)	127	133	126	130	137	130	122	118
N(Buy)	64	66	67	64	87	78	69	70
N(Sell)	63	70	59	66	50	52	53	48
Annualized return (%)	18.0	16.0	6.9	29.2	10.2	13.2	0.5	7.8
Break-even cost (%)	1.02	0.87	0.40	1.62	0.53	0.73	0.03	0.48
(1,150,0)								
N(Trading)	90	88	83	82	84	77	88	86
N(Buy)	50	48	42	42	68	53	51	54
N(Sell)	40	40	41	40	16	24	37	32
Annualized return (%)	9.2	12.9	3.1	19.4	9.0	3.3	4.4	7.3
Break-even cost (%)	0.74	0.52	0.27	1.71	0.78	0.31	0.36	0.61
(1,150,0.01)								
N(Trading)	76	71	67	64	72	61	71	61
N(Buy)	38	38	35	30	57	40	38	42
N(Sell)	38	33	32	34	15	21	33	19
Annualized return (%)	5.2	11.6	-2.0	21.0	10.0	3.2	1.9	5.8
Break-even cost (%)	0.50	1.18	-0.21	2.37	0.98	0.38	0.19	0.69
(1,200,0)								
N(Trading)	76	74	71	68	78	66	71	68
N(Buy)	41	41	34	33	66	46	41	43
N(Sell)	35	33	37	35	12	20	30	25
Annualized return (%)	9.1	9.4	4.3	16.0	8.3	4.0	3.1	5.9
Break-even cost (%)	0.86	0.91	0.44	1.70	0.77	0.44	0.32	0.63
(1,200,0.01)								
N(Trading)	64	60	58	56	67	52	56	49
N(Buy)	30	31	29	25	55	35	29	36
N(Sell)	34	29	29	31	12	17	27	13
Annualized return (%)	7.2	6.7	-0.4	16.4	8.8	3.6	3.5	7.2
Break-even cost (%)	0.81	0.81	-0.04	2.10	0.94	0.50	0.46	1.06

Note: N(Buy) and N(Sell) are the number of buy and sell signals generated by each rule. N(trading) is the number of trades required to shift a position from “double” to “out” or vice versa. The annualized return for each rule is the annualized buy-sell spread from the “double-or-out” strategy in excess of interest rates (and the buy-and-hold return by construction), and is calculated as $\pi_i^B + \pi_i^S$ (defined in Section 3.4.2) divided by the number of years in the sample. Break-even costs are computed as the differential between buy and sell means divided by twice the number of trades, and represent the one-way percentage trading costs that would just eliminate the ex post difference between accumulated returns to following the trading rule and to a buy-and-hold strategy.

Chapter 4: Testing Dividend Announcement Strategies in the UK for Statistical Arbitrage

4.1 Introduction

Numerous empirical studies in the literature document the profitability of trading strategies which exploit perceived persistent market anomalies. Such strategies can be broadly classified either as return-based which try to exploit time series patterns in security returns, or as trading strategies that capture, or could potentially capture, excess returns following various corporate events (announcements). The most prominent examples of the former class are the momentum strategies of Jegadeesh and Titman (1993) over “short to medium” investment horizons, and the contrarian strategies of De Bondt and Thaler (1985, 1987) over “long horizons”.¹ The former authors document average excess returns of 12 per cent per year from buying well-performing stocks and selling poor-performing stocks, where excess returns are defined relative to a standard capital asset pricing model. A compilation of 120 momentum and contrarian strategies over different trading horizons is contained in Conrad and Kaul (1998), who find that nearly 50% of the strategies they examine produce statistically significant profits, transaction costs aside. Chan et al. (1996) also find that momentum portfolios formed on the basis of past returns and earnings announcements yield excess returns, even after transaction costs. Lakonishok et al. (1994) report that contrarian strategies based on buying value (undervalued) and selling glamour (overvalued) stocks identified with variables such as price earnings ratios, cash flow, and growth in earnings, sales, and cash flow, produce excess returns of 10-11 per cent per year relative to the three-factor Fama-French model (1993).

In the second category we can find, for example, a trading strategy involving dividend

¹ “Short to medium” in the anomalies literature typically refers to 3 to 12 months investment horizons and “long” to investment horizons longer than a year.

initiations and omissions by Michaely et al. (1995). In addition, profitable strategies can be constructed to take advantage of long-term abnormal stock returns following seasoned equity offerings (SEOs) and open market share repurchases (Eberhart and Siddique (2002), Ikenberry et al. ((1995), (2000))), Loughran and Ritter (1995)), initial public offerings - IPOs - (Ritter (1991)), new exchange listings (Dharan and Ikenberry (1995)), as well as R&D increases (Eberhart et al. (2003)).²

The aforementioned studies seem to uncover evidence which contradicts the Efficient Market Hypothesis (EMH); however, they are all compromised by the joint hypothesis problem ubiquitous in tests of the EMH. Fama (1998) cautions against rejecting market efficiency as abnormal return measures like the risk-adjusted alpha are particularly vulnerable to incorrectly specified equilibrium models for expected returns. Similarly, Mitchell and Stafford (2000) argue that abnormal return estimates may be biased if factor model estimates of expected returns are incomplete in measuring risks. Moreover, Fama argues that long-term anomalies appear sensitive to the statistical methodology utilized, and casts doubt on the ability of single t-tests for the significance of risk-adjusted alphas to determine a rejection of the EMH. In particular, Fama and Mitchell and Stafford point out that buy-and-hold returns following corporate events are an inappropriate metric for computing long-term returns; event-time returns have a cross-sectional dependence problem mainly due to overlapping data that biases the standard error downwards, which consequently biases tests using this return metric towards findings of significant abnormal returns.

²Recent evidence suggests we should be sceptical about reported long-term anomalies, whose robustness should be re-evaluated using different methodologies, sample periods, asset pricing models, and international data. Mitchell and Stafford (2000) employ a calendar-time methodology and procedures that account for documented biases in the three-factor model of Fama and French (1993) to find no reliable evidence of any long-term anomaly following corporate acquisitions, share repurchases, and SEOs. Similarly, Brav et al. (2000) and Eckbo et al. (2000), argue that firms become less risky following SEOs due to a decrease in leverage, and as a result would command a lower expected return when compared to control firms, which could explain the apparent underperformance in prior studies. Moreover, Brav et al. claim to resolve the IPO anomaly by using a control portfolio matched on size and book to market characteristics.

Hogan et al. (2004) have developed a methodology to test for long-term anomalies that addresses both the statistical criticisms and circumvents the joint hypothesis problem. The methodology is based on the concept of statistical arbitrage (SA), which they define as a long horizon trading opportunity that, in the limit, generates a riskless profit. Statistical arbitrage is defined without reference to any equilibrium model, which is a prerequisite for an efficient market (Jarrow (1988)), and thus its existence implies that the market cannot be efficient for *any* model of market equilibrium. As such, statistical arbitrage enables rejection of market efficiency without invoking the joint hypothesis of an equilibrium model. In addition, the statistical arbitrage test does not rely on a single t-ratio on the mean of excess returns to reject market efficiency, but instead conducts multiple significance tests on both the mean and volatility of the trading profits series. In fact, buy-and-hold portfolio returns, which better reflect investor experience than calendar time methodologies, are translated into a time series of incremental trading profits computed over short horizons. Hogan et al. apply this methodology to momentum and value trading strategies using US data from 1965 to 2000 to find evidence in favor of statistical arbitrage for nine of the sixteen momentum strategies and five of the twelve value strategies they examine. They conclude that momentum and value strategies provide strong evidence against the EMH.

In this Chapter, the primary focus is to investigate an anomaly associated with corporate announcements, namely with “extreme” changes in dividend policy, such as dividend initiations (including dividend resumptions) and dividend omissions. There have only been a handful of academic studies to investigate the long-term impact on stock market performance of such announcements, least so for the UK market, whereas many more studies look at the short-term performance around the announcement day. In particular, we are aware of no study that consistently evaluates the feasibility of trading strategies designed to exploit abnormal performance relative to the market following dividend an-

nouncements, even in a US context.³ By testing trading profits from such strategies for SA, we can determine whether or not the market adjusts efficiently to such corporate events. Moreover, the risk characteristics of the strategies are monitored to assess whether the generated trading profits pass the statistical arbitrage test of Hogan et al. (2004). Thus, unlike Boehme and Sorescu (2002), we are able to conclude more confidently whether any abnormal behavior is consistent with the EMH or not.

The outline of this Chapter is: In Section 4.2 we discuss the limits of arbitrage which partly motivate SA trading strategies. In Section 4.3 we introduce the notion of SA, while in Section 4.4 we review the empirical evidence on “relative value” SA. Section 4.5 investigates the link between SA and market efficiency, while Section 4.6 presents the Hogan et al. (2004) framework and definition of SA, with a view to testing “market anomalies” for SA, and thus, market efficiency. Section 4.7 reviews the empirical evidence regarding the predictions of the signaling theory of dividends, particularly in the long-term, providing the motivation for the empirical part of the chapter. Section 4.8 analyzes the empirical methodology employed and presents the SA test. Section 4.9 presents the data and Section 4.10 the “dividend announcement trading strategies” employed. Section 4.11 discusses the empirical results and finally Section 4.12 concludes the chapter.

4.2 The Limits of Arbitrage

A *pure arbitrage opportunity* (PAO) is a zero cost trading strategy that offers the possibility of a gain with no possibility of a loss (Bondarenko (2003)). Such a strategy involves the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices (Sharpe and Alexander (1990)). The

³Michaely et al (1995) actually construct such a trading strategy, but the purpose is to evaluate the robustness of their excess returns calculations. Therefore, they do not integrate transaction costs into their analysis, and only evaluate the percentage returns of the strategy for a one year horizon. Since their strategy involves trading after *each* dividend announcement, transaction costs are very likely to be prohibitive from a trading point of view.

appropriate “lock-in” transaction consists of buying the underpriced asset(s), financed from the sale of the overpriced asset(s). Therefore, in theory, arbitrage requires no capital and entails no risk: The net future cash flows from such a transaction are assuredly zero, while profits are available up-front.

Arbitrage acts as an error-correction, or negative feedback, effect, in that the buying and selling activities of arbitrageurs will tend to reduce the magnitude and duration of mispricings which the arbitrageur is attempting to exploit. Thus, the effect of arbitrage activities is to bring prices back to fundamental values and to keep markets efficient. In an efficient market there will exist no riskless arbitrage opportunities which allow traders to obtain profits by buying and selling equivalent assets at prices that differ by more than the transaction costs involved in making the trades. This forms the basis of the “no-arbitrage” pricing approach used in the pricing of financial derivatives such as options, forwards, and futures; the key idea being that the price of the derivative can be obtained by calculating the cost of the appropriate replicating portfolio.

As is well known, the existence of PAOs is incompatible with a competitive equilibrium in asset markets. The fundamental theorem of the financial theory establishes a link between the absence of PAOs and the existence of a positive pricing kernel which supports securities prices (see Section 4.5). Consequently, the absence of PAOs is a critical premise of traditional equilibrium asset pricing models such as the CAPM (Sharpe (1964)) and APT (Ross (1976)).

Given the importance of arbitrage in financial theory, it is important to ascertain how well the textbook description of arbitrage (a PAO) approximates reality. Shleifer and Vishny (1997) argue convincingly that the model of capital-free arbitrage simply does not apply. They give the example of two Bund futures contracts to deliver the same amount in face value of German bonds at time T , one traded in London and the other in Frankfurt. If at some point in time t , the price of the Frankfurt contract exceeds the

price of the London contract, an arbitrageur would sell a futures contract in Frankfurt and buy one in London, recognizing that at time T he is perfectly hedged. To do so, at time t , he would have to put an initial margin both in London and Frankfurt. If soon after t ($t + s$) the prices of the two contracts converge as the market returns to efficiency, the arbitrageur can close out his position, make a profit and receive his good faith money (the initial margin) back as well (a near-textbook case). However, if at $t + s$, the price of the Frankfurt contract moves further away from the price in London (which assume for simplicity stays constant), the arbitrageur will be charged by the Frankfurt exchange the difference in the price of the Frankfurt contract between times $t + s$ and t . Even if eventually the prices of the two contracts converge and the arbitrageur makes money, in the short-term he loses money and needs more capital. The textbook definition of arbitrage does not allow for intermediate losses. If the arbitrageur can access the extra capital he still makes money with probability one (i.e. the trade is eventually risk-free). If, however, he is capital-constrained, he may run out of money and have to liquidate his position at a loss!

One way to mitigate these concerns is to employ the model of arbitrage implicit in Fama's (1965) classic analysis of efficient markets and in traditional asset pricing models, whereby the market is populated with a very large number of tiny arbitrageurs each taking an infinitesimal position against the mispricing in a variety of markets. Because positions are so small, capital constraints are not binding and arbitrageurs are effectively risk neutral towards each trade. Their collective actions, however, drive prices towards fundamental values.

The problem with this approach is that it is not very realistic. There is a competitive "arms race" among arbitrageurs such that not only theoretically-motivated "riskless" strategies are self-limiting, but also are restricted to relatively privileged market players who have the knowledge and information to engage in arbitrage, are geared to trade

quickly, at low cost, and with sufficient financial leverage to make the exercise worthwhile. More commonly, the relatively few professionals who conduct arbitrage use the resources of outside investors to take large positions, introducing an agency relationship between themselves and investors. Shleifer and Vishny (1997) present an agency model of arbitrage whereby resources available to arbitrageurs by investors are limited, and based on arbitrageurs' past performance (termed performance-based arbitrage). This means that although arbitrageurs would like to allocate funds based on expected returns from trades, investors may rationally allocate money based on the past returns of arbitrageurs. In the Bund example, an arbitrageur would generally increase his position if London and Frankfurt prices move further out of line, as long as he has the capital. Investors will observe the arbitrageur losing money when the mispricing the arbitrageur has bet against gets even worse, may infer that he is not competent, and refuse to provide him with more capital - or even withdraw some capital - even though the expected return from the trade has increased. The link between greater mispricing and higher expected returns is thus broken by those allocating capital. Therefore, when arbitrage requires capital, arbitrageurs can become most constrained when they have the best opportunities. Shleifer and Vishny show that performance-based arbitrage is particularly ineffective when prices are significantly out of line and arbitrageurs are fully invested, resulting in arbitrageurs liquidating positions when their participation is most needed, limiting the effectiveness of arbitrage to achieve market efficiency.

Also, in practice, the situation is even more complicated by the fact that arbitrage which is technically riskless can ultimately involve some risk. In the Bund example, the two contracts may have somewhat different trading hours, settlement dates, and delivery terms. In general, risk is introduced by, for example, uncertain future dividend rates, market volatility during the short time required to carry out the lock-in trades (slippage), failure to "fill" all legs of the trade thus leaving a residual "unhedged" risk, etc. Notably,

an important source of risk in arbitrage activity is “basis risk” caused by fluctuations in the difference between spot and futures prices prior to the expiration date. “Even the simplest trade then becomes a case of what is known as risk arbitrage” (Shleifer and Vishny (1997), p.36). In risk arbitrage, an arbitrageur does not make money with probability one, and may need capital both to execute the trades and cover potential losses.

Therefore, unlike in the textbook model, practical arbitrage strategies are risky, may involve (intermediate) losses and require capital. In fact, the majority of arbitrage strategies are at least implicitly reliant on the statistical properties of the mispricing or deviation from the fair price relationship. For example, the attraction of index arbitrage strategies lies in the tendency for the basis risk to “mean revert” or fluctuate around a stable level. The recognition that practical arbitrage strategies both involve risk and rely upon favorable statistical properties of the mispricing dynamics leads to a more general class of arbitrage strategies known as “statistical arbitrage”.

4.3 The Notion of Statistical Arbitrage

The premise of SA is that it may be possible for statistical regularities in *relative* asset prices to be exploited as the basis of profitable trading strategies, irrespective of the presence or absence of a theoretical fair-price relationship between the set of assets involved. While clearly subject to a higher degree of risk than “true” arbitrage strategies, such statistical arbitrage opportunities (SAOs) are likely to be both more persistent and prevalent in financial markets. More persistent because risk-free arbitrage opportunities are rapidly eliminated by market activity. More prevalent because in principle they may occur between any set of assets rather than solely in cases where a suitable risk-free hedging strategy can be implemented.

An idea of the risks involved in SA strategies can be obtained by focussing on one of

the simplest of such strategies, namely “pairs trading”. This relies on the identification of pairs of financial assets the prices of which “move together” in the long term, with temporary deviations from the long term correlation which exhibit a mean-reversion pattern. In pairs trading, the arbitrageur will buy an underpriced asset and sell an overpriced asset on the assumption that the long-term relationship will be restored. However, there is no “expiration date” on which the prices are defined to be equal. The price correction may occur over a long period, with the deviation first moving against the arbitrageur and generating short-term losses or “draw downs”. Moreover, the expected price correction may never occur, implying that any underlying relationship between the two assets has either broken down completely or at least evolved to a new equilibrium level.

Despite these risks, the substantial opportunities presented in cases where such relationships persist over time have made relative value statistical arbitrage strategies increasingly attractive. Part of this attraction derives from the fact that such trading strategies are broadly *market neutral* (as are PAOs); appropriately constructed relative prices will be largely independent of market wide sources of risk and will instead highlight the *asset specific* aspects of the price dynamics. Combinations of assets amenable to SAOs exploit predictable components in asset price dynamics in a manner which is (statistically) independent from market dynamics. Burgess (1999) points out that as the asset-specific component of the dynamics is not directly observable by market participants, it is plausible that regularities in dynamics may exist which have not yet been “arbitraged away” by market participants.

The three essential components for “relative value” SA trading models are (Burgess, 1999):

- construction of statistical fair-price relationships between assets through time-series analysis of historical price movements such that the “mispricings” have a (statistically significant) predictable component.

- identification of statistical arbitrage opportunities (involving forecasting of changes in *relative* asset prices).
- implementation of appropriate trading strategy (buy asset (or combination of assets) forecasted to *outperform*, sell asset (or combination of assets) forecasted to *underperform*).

The modeling challenge of the first component could be stated as “given an asset (or portfolio) X_t to identify an appropriate combination of assets to form the corresponding statistical hedge, or “synthetic asset”, $SA(X_t)$ ”. The objective of the second, predictive modeling, stage, would be to “create models capable of (largely) predicting the changes in the “statistical mispricing” between the two portfolios, i.e. $E[payoff(X_t - SA(X_t))]$ ”. Finally, a trading strategy to effectively exploit the predictive information which returns significantly positive profits (after transaction costs), whilst simultaneously controlling the risks involved (both due to asset price dynamics in general and the specific arbitrage model in particular), is warranted.

4.4 Empirical Evidence on “Relative Value” Statistical Arbitrage

Trading strategies that have been termed “statistical arbitrages” by risk-arbitrageurs are not a last moment development in financial markets. Wall Street investment banks have been using “market-neutral” investment strategies since the early 1980s with considerable success. The Morgan Stanley group set up by Wall Street quant Nunzio Tartaglia reportedly made a \$50million profit for the firm in 1987 with mainly short-term speculation strategies such as “pairs trading” - the group was disbanded though in 1989 after a couple of bad years -. The aforementioned strategy, for example, is among the proprietary

SA tools currently used by institutional traders and hedge funds, which are nowadays the most fervent searchers in statistical arbitrage trading strategies.

Despite the high practical relevance of SA, there have been, to the best of our knowledge, only a handful of empirical studies in the academic literature which examine SA strategies. Poitras ((1987), (1997)) looked for statistical arbitrage opportunities in the commodities market. He investigated the relationship between the cost of carry of gold and of Eurodollar futures to find that when the former was either too close or too far away from the Eurodollar interest rate, then a profit could be made by taking a trading position and closing it out once the relationship had normalized. He found that such arbitrage profits were available between 1982 and 1985, and again in 1988 and 1989.

As far as stock markets are concerned, Gatev et al. (1999) evaluated the profitability of “pairs trading” rules with arbitrary six-month trading periods using daily US stock price data over the period 1962 through 1997. They identified pairs of stocks that are close economic substitutes and whose prices have the highest correlation over the course of a twelve-month period. They then follow a trading rule that places a long position in one stock and a short position in the other stock if the spread in the current prices has diverged by more than two standard deviations from the mean value found using historical data. The trade is then closed out if the spread moves back in line with the model, and all positions are closed out at the end of six months regardless of whether or not the spread has converged. Gatev et al. documented average annualized excess returns of up to 12 per cent for a number of self-financing portfolios of the most highly correlated pairs of stocks, which are only partly explained by mean reversion or the bid-ask bounce. Taking transaction costs into account, pairs trading yields reduced - but still positive and significant - returns. Moreover, the pairs trading portfolios are virtually uncorrelated with the S&P500 index and much less volatile. Alexander and Dimitriu (2002) propose a “cointegration” SA strategy, the success of which rests on identifying

a stationary linear relationship between the market index and (some) of its component stocks. A simple tracking portfolio is first constructed using the “cointegration weights”. To exploit the tracking potential of cointegrated portfolios, a “plus” and “minus” artificial index is constructed so as to linearly overperform and underperform the market index respectively by a given amount per annum. Then, self-financing long-short strategies can be applied by being long on a portfolio tracking the “plus” benchmark and short on a portfolio tracking the “minus” benchmark. Alexander and Dimitriu apply self-financing SA strategies to the Dow Jones Industrial Average stocks to find that the most successful strategies returned approximately 10 per cent per annum net of transaction costs, with roughly 2 per cent annual volatility and negligible correlation with the market.

Amman and Herriger (2002) investigated whether option markets are efficient with regards to the relative pricing of similar risk as demonstrated by the relative implied volatilities of at-the-money options on highly correlated US indices. If two indices are highly correlated, then a relationship should exist between the volatility levels of the indices. The authors first calculated the correlations between eleven US stock indices, and identified the pairs of indices most highly correlated. For each of these pairs, they studied the relationship between the returns of the two indices using an OLS regression, estimating statistical boundaries for the OLS coefficients (intercept ($\hat{\beta}_1$) and slope ($\hat{\beta}_2$)) to account for time variation. The model generated was then transformed to give a model of the relationship between the realized volatilities of the two indices, and the predictive capacity of the boundaries for historical volatilities was confirmed with out-of-sample tests. The model was then applied to the implied volatilities of options on the stock indices, for which a similar relationship should prevail, and the boundaries calculated for the relative future volatility should also hold for the relative implied volatility of options on the two indices. If the implied volatilities broke the boundary, then this was identified as a possible theoretical mispricing, and hence a trading opportunity. The arbitrage

trade involved selling one at-the-money option of the overvalued index and buying a $\hat{\beta}_2$ -adjusted amount of at-the-money options of the undervalued index. Amman and Herriger found that a large number of boundary violations arose in the data studied, but when bid-ask spreads and transaction costs were taken into account, only a small number of those deviations could be flagged as presenting a SAO.

4.5 Statistical Arbitrage, Securities Prices and Market Efficiency

SAOs offering the possibility of profits at the expense of minimum (or negligible) risk should not endure over time if markets are efficient, which does not seem to be the case in the Gatev et al. (1999) and Alexander and Dimitriu (2002) studies. In fact, as mentioned in the introduction to this chapter, a number of influential studies in the market anomalies literature provides evidence on stock price behavior that seems to contradict the EMH. However, one cannot ascertain how “anomalous” this behavior actually is, as these studies are always rejections of a joint hypothesis - a particular equilibrium model and the notion of an efficient market. The literature has only recently provided us with methodologies for attempting to resolve this ambiguity, which, nonetheless, are not general enough to be employed in all market efficiency tests.

In particular, Bondarenko (2003) and Hogan et al. (2004) utilize the SA terminology to derive empirically testable hypotheses for the existence of SAOs, the presence of which enables the rejection of market efficiency without invoking the joint hypothesis of an equilibrium model. This is so because SA is defined without reference to any equilibrium model, and therefore, its existence is inconsistent with market equilibrium, and, by inference, market efficiency (Jarrow, 1988).

Generalizing the definition of arbitrage to include SA has important pricing implica-

tions. To put things into perspective, consider the simple case of a finite-horizon economy with a finite number of trading dates, indexed by $t = 0, 1, \dots, T$, and a finite number of primary assets that are traded in a frictionless and competitive market. At time t , the state of the economy is represented by a random variable ξ_t , and the prices of the assets depend on the state ξ_t . The history of states up to time t determines the market information set $I_t = (\xi_1, \dots, \xi_t)$. We distinguish between “elementary” and “final” states, whereby the elementary state $I_T \in \mathcal{I}_T$ provides a complete description of uncertainty from time 1 to T , while the final state $\xi_T \in \Xi_T$ describes the price relevant uncertainty on the final date.⁴ By trading primary assets, investors can generate various payoffs at time T . Specifically, we can consider a self-financing trading strategy that pays a random, path-dependent payoff $Z_T = Z(I_T)$. Let Z_t denote the value of such a generic payoff at time t .⁵ Alternatively Z_t can be interpreted as the time t price of a general European-style derivative security with a path-dependent payoff $Z(I_T)$.

A zero-cost trading strategy with a payoff $Z_T = Z(I_T)$ is a PAO if $E[Z_T/I_0] > 0$, and $Z_T \geq 0$ for all I_T . Harrison and Kreps (1979) show that a pricing kernel $m(I_T) > 0$ exists if and only if there are no PAOs (the first fundamental theorem of asset pricing). The absence of PAOs under the EMH implies that security prices (Z_t) satisfy the restriction

$$E[Z_s m_s / I_t] = Z_t m_t, \quad t \prec s \preceq T \quad (4.1)$$

To test this restriction, one needs to know the pricing kernel (equilibrium pricing model). However, as the pricing kernel is unobservable, tests of the EMH based on (4.1) suffer from a joint hypothesis problem. Rejections may be the outcome of a truly inefficient

⁴For example, one can interpret ξ_t as the value of the market portfolio at time t , or more generally, as a vector of prices of traded assets and other economic factors (such as interest rates), with I_T representing the complete time series path.

⁵Formally, suppose there are n primary assets and let $d_t = (d_t^1, \dots, d_t^n)$ and $p_t = (p_t^1, \dots, p_t^n)$ denote their dividends and (ex-dividend) prices at time t . One of the assets may represent a risk-free bond. A self-financing trading strategy (dynamic portfolio) is a nonanticipating process $\theta_t = (\theta_t^1, \dots, \theta_t^n)$, where θ_t^i represents the number of shares of asset i held at time t , such that $\theta_{t-1}(p_t + d_t) = \theta_t p_t$ for all $t \geq 1$. The value process of the strategy is defined as $Z_t = \theta_t p_t$.

market or an incorrectly assumed pricing kernel . Generally, the pricing kernel m_T may depend on the complete price history, or $m_T = m(I_T)$. Except for the positivity constraint, the function $m(I_T)$ has to satisfy no other conditions. This could be economically “unreasonable” as values of the pricing kernel for two “close” price histories are allowed to be arbitrarily far apart. Also, just the absence of PAOs assumption with no restrictions on the pricing kernel may yield pricing implications that are too weak to be practically useful; for example, when valuing options in incomplete markets, the no-arbitrage bounds on option prices are typically very wide (Bondarenko, 2003).

To strengthen pricing implications, particularly in incomplete markets, a number of papers have extended the standard definition of arbitrage, albeit in alternative ways. Cochrane and Saa-Requejo (2000) argue that if efficient markets rule out not only PAOs but also investment opportunities with high Sharpe ratios, or “good deals”, then tighter pricing implications are obtained - via imposing an upper bound on the pricing kernel volatility - . Bernardo and Ledoit (2000) exclude *approximate arbitrage opportunities*, i.e. investments with maximum gain-loss ratios (where gain (loss) is the expectation of the positive (negative) part of the excess payoff computed under a benchmark risk-neutral measure). Both these approaches also investigate trading opportunities that generalize the definition of arbitrage without specifying a particular market equilibrium model. The studies by Bondarenko (2003) and Hogan et al. (2004) are related to this literature, as there is a similar generalization of arbitrage to include SAOs. In both of these approaches, there is no need to preclude opportunities whose attractiveness - as measured by Sharpe ratios, gain-loss ratios, etc - exceed some ad-hoc threshold. However, the two aforementioned studies differ in that they have different axioms in their respective definitions of SA and different empirical applications: The approach of Hogan et al. is intended for applications to persistent market anomalies while Bondarenko investigates option pricing in incomplete markets. Moreover, unlike the earlier studies, Hogan et al.’s generalization

of arbitrage is defined under the observed probability measure, rather than a collection of probability measures.

Bondarenko (2003) argues that excluding not only PAOs, but also SAOs, imposes a very powerful restriction on security prices which is independent of the pricing kernel. A SAO is defined as a zero-cost trading strategy for which the expected payoff is positive and the conditional expected payoff in each final state ξ_T is nonnegative. Formally, let $I_t^{\xi_T} := (I_t; \xi_T) = (\xi_1, \dots, \xi_t; \xi_T)$ denote the augmented information set, which in addition to the market information at time t , also includes the knowledge of the final state of the economy.

Definition 1 *A zero-cost trading strategy with a payoff $Z_T = Z(I_T)$ is called a SAO if*

- (i) $E[Z_T/I_0] > 0$, and
- (ii) $E[Z_T/I_0^{\xi_T}] \geq 0$ for all ξ_T

Unlike a PAO, a SAO can have negative payoffs in some elementary states I_T , as long as the average payoff for each ξ_T is nonnegative. Implicit in the definition of a SAO is the assumption that many different histories I_T correspond to a given final state ξ_T , meaning that a path-dependent strategy may have uncertain payoffs in ξ_T . It is clear that any PAO is a SAO, but the reverse is not true. Bondarenko proves that if and only if there are no SAOs, then there exists a *path independent* pricing kernel $m(\xi_T) > 0$. Path independence implies that not only PAOs but also more general SAOs cannot exist. The absence of SAOs imposes a new restriction on the dynamics of security prices, a rejection of which would constitute a rejection of market efficiency. To illustrate the argument, Bondarenko considers three dates $t = 0, 1$, and 2 . For fixed x , let δ^x denote the Arrow-Debreu security which at $t = 2$ pays \$1 if the final state of the world is $\xi_2 = x$ and zero otherwise. Thus the security's price at time t is equal to the risk-neutral probability $h_t(x)$. Consider two strategies that both invest one dollar in δ^x : the first strategy buys $1/h_0(x)$ shares at $t = 0$ and the second buys $1/h_1(x)$ shares at $t = 1$. The payoffs are:

$$Z^I = \begin{Bmatrix} \frac{1}{h_0(x)}, & \xi_2 = x \\ 0, & \xi_2 \neq x \end{Bmatrix} \quad Z^{II} = \begin{Bmatrix} \frac{1}{h_1(x)}, & \xi_2 = x \\ 0, & \xi_2 \neq x \end{Bmatrix}$$

The strategies have the same zero payoff in all states $\xi_2 \neq x$. This means that they must also pay the same expected payoff conditional on $\xi_2 = x$, otherwise $(Z^I - Z^{II})$ or $(Z^{II} - Z^I)$ will be a SAO. Therefore,

$$E[Z^I/I_0^x] = E[Z^{II}/I_0^x] \quad (4.2a)$$

or

$$E\left[\frac{1}{h_1(x)}/I_0^x\right] = \frac{1}{h_0(x)} \quad (4.2b)$$

That is, if we consider an Arrow-Debreu security which eventually matures in-the-money, then the inverse of its price follows a martingale process. The result must hold for *all* pricing kernels $m(\xi_2) > 0$. A similar argument can be used to show that for a general security with a payoff $Z(I_2)$ at $t = 2$,

$$E\left[\frac{Z_1}{h_1(x)}/I_0^x\right] = \frac{Z_0}{h_0(x)} \quad (4.3)$$

Stating the result formally, let $x \in \Xi_T$ denote a possible final state and let $T' < T$. Assuming that the pricing kernel is path independent, and that for all histories $I_{T'}$ the risk neutral probability $h_{T'}(x) > 0$,⁶ then if EMH holds, securities prices deflated by

⁶The assumption of positive risk-neutral probabilities is just a technical assumption which ensures that the ratio inside the conditional expectation operator in equation 4.3 is always well defined. It precludes situations when at some point $s \leq T'$ investors learn that state x cannot possibly happen and thus $h_s(x) = 0$.

the risk-neutral probability of the final state $h_t(x)$ are martingale processes under the objective probability measure with respect to the augmented information set I_t^x . That is,

$$E \left[\frac{Z_s}{h_s(x)} / I_t^x \right] = \frac{Z_t}{h_t(x)}, \quad t < s \leq T' \quad (4.4)$$

The restriction in equation (4.4) makes no reference to the pricing kernel; it is completely model-free. Thus, one can be completely agnostic about the true equilibrium model and still be able to test the EMH provided the assumption of path independence holds. Actually, the author shows that this all important assumption is not restrictive as it is satisfied by many popular asset pricing models such as the CAPM, multifactor pricing models, the Black-Scholes model, and others. It is also preference-independent, can be tested in samples affected by selection biases, and continues to hold even when investors' initial beliefs (priors) about the final state are mistaken (provided investors' *conditional* beliefs are correct, i.e. rationally updated). It also holds in general economic environments with many assets, incomplete markets, continuous trading, etc. However, Bondarenko's intuitive proposition has some disadvantages with respect to the practical implementation of the restriction. First, expression (4.4) has the unusual feature of conditioning on future information. As the author notes, this implies that testing the restriction cannot be conducted in "real time"; the disadvantage is that one must wait until the final state is revealed. Also, testing requires that the risk-neutral probability of the final state, $h_t(x)$, is available; even though the risk-neutral density is not directly observable in financial markets, it is implicit in prices of derivative securities, and in particular, can be estimated from prices of traded options with different strikes. This, however, is conditional upon the existence of well-developed liquid option markets, which thing restricts application of Bondarenko's proposition mainly to investigation of option pricing. The author implements this methodology using S&P500 index futures options data over the period 1987 to 2000. First, he documents extraordinary high and statistically significant average excess

returns by selling unhedged put options one month before maturity, suggesting that puts are grossly overpriced. This is verified by estimating risk-neutral densities from prices of standard call options and testing the restriction in (4.4). The restriction is strongly rejected, pointing towards inefficiency of the US options market.

4.6 Statistical Arbitrage and Market Anomalies

Relatively recent research in finance has uncovered a number of so called anomalies, in which particular investment strategies have historically earned higher returns than those justified by their systematic risk, as measured by asset pricing models. The EMH approach to these anomalies is that the model of asset pricing that made the evidence look anomalous must have been misspecified in the first place.⁷ As argued in Section 4.2, the theoretical underpinnings of the EMH approach to arbitrage are based on the highly implausible assumption of many diversified arbitrageurs. In reality, arbitrageurs are few, highly specialized, far from diversified, institutions which care about total risk, not just systematic risk. Since the trading strategies of these investors determine equilibrium excess returns, it is possible that idiosyncratic risk, whether fundamental or noise trader related, is also a potential determinant of securities prices. Shleifer and Vishny (1997) argue that in this setting, a different explanation for persistent market “anomalies” is plausible: Because of the relatively long horizon required to secure positive returns with a high probability for many of the anomalies strategies, and the possibility of high volatility of the hedge portfolio over short horizons, such trading strategies may be shunned by specialized arbitrageurs who cannot hedge this risk - even if idiosyncratic - in the particular market segment. In extreme situations, arbitrageurs trying to eliminate the anomaly

⁷For example, Fama and French (1992) argue that the capital asset pricing model is misspecified, and that the value/glamour anomaly can be explained away by considering an extra systematic risk factor other than the market on which high book to market stocks (which earn higher returns than low book to market stocks) have a high loading. They call this factor the distress factor and argue that the portfolio of high book to market stocks is itself a proxy for it.

may lose enough money that they have to liquidate their positions.⁸ Therefore, market anomalies that have a high degree of short term unpredictability which makes betting against them risky for specialized arbitrageurs, can persist over the long term.

The Shleifer and Vishny (1997) paper paves the way for re-evaluating the empirical challenges to the EMH paradigm posed by long term market anomalies. Notably, Hogan et al. (2004) propose a methodology for resolving the dichotomy confounding traditional EMH tests. This is based upon extending standard arbitrage to its infinite horizon counterpart (which embodies the essence of statistical arbitrage), and appealing to long horizon trading strategies to test the EMH. To define a statistical arbitrage, the authors draw on the limiting arbitrage opportunity used to construct Ross' (1976) Arbitrage Pricing Theory (APT), the difference being that Ross' APT is a cross-sectional limit at a point in time, while a statistical arbitrage is a limiting condition *across* time. This difference necessitates working with the *discounted* cumulative profits over "*long*" time horizons (while Ross' APT is appropriate in an economy with a "large" number of assets). Trading strategies with positive expected discounted profits are not sufficient to declare a persistent anomaly a source of market inefficiency. Instead, over time, analogous to cross-sectional diversification in the APT, the variance of the trading profit series must be "diversifiable", that is, approach zero. Only then can a trading strategy be classified as a SAO.

The existence of SAOs rejects all candidate models of market equilibrium, and is thus incompatible with market efficiency. A SAO allows for intermediate losses, and for risk that arbitrageurs may have to face in the short term, which is a welcome flexibility for persistent market anomalies whose probability of losing money is positive at a given finite point in time. Nevertheless, the all-important caveat that a statistical arbitrage

⁸Shleifer and Vishny (1997) argue that something along these lines happened with commercial banking stocks in the US between 1990-1991. As the prices of these stocks fell sharply, value arbitrageurs invested heavily in these stocks. However, as the prices kept falling, many lost their funds under management and had to liquidate their positions. As a result, many value funds found themselves without the necessary capital to profit from the subsequent recovery of these stocks.

strategy converges to an arbitrage strategy in the limit (and consequently makes money with probability one), while reducing its time-averaged variance in the process, essentially mitigates the concerns of Shleifer and Vishny (1997) about “risky” arbitrage. We provide below a brief exposition of Hogan et al.’s (2004) framework which leads to their definition of statistical arbitrage.

Let $(\Omega, F, (F_t : t \geq 0), P)$ be a filtered probability space over an infinite horizon $[0, \infty]$, satisfying the usual conditions. P is the statistical (observed) probability measure. Traded in the economy are a stock S_t and a money market account B_t initialized at a dollar ($B_0 = 1$). Any spot rate process consistent with an arbitrage free evolution is acceptable.⁹ Let the stochastic process $(x(t), y(t) : t \geq 0)$ represent a *zero initial cost* ($x(0)S_0 + y(0) = 0$), *self-financing* trading strategy (i.e. no net cash inflow or outflow following the strategy’s construction) involving $x(t)$ units of stock and $y(t)$ units of a money market account at time t . The strategy is formulated using only available information at time t (such as past returns, dividend announcements, sales growth, etc.)¹⁰ The stock itself can be a (zero-cost) self-financing portfolio consisting of long and short positions in the risky assets, as is usually the case for trading strategies designed to exploit persistent anomalies.¹¹

Let the process $V(t)$ denote the cumulative trading profits at time t that are generated by such a trading strategy $(x(t) : t \geq 0)$,¹² and $v(t)$ be the discounted value of the cumulative trading profits, $v(t) = V(t)/B_t$. A SAO requires $v(t)$ to satisfy the four axioms stated in Definition 2 below:

⁹We use $B_t = \exp(rt)$, where r represents the risk-free rate and t is the time index.

¹⁰Note the difference between this approach and the one in Bondarenko (2003) which involves conditioning on future information

¹¹The anomalies literature actually deals with non self-financing trading strategies, that can be transformed into self-financing, by, say, investing accumulated gains in the money market account (possibly reducing the average variance of $v(t)$ as a consequence), or simply reducing the short position by the amount of the accumulated gain, or even investing the proceeds in a portfolio that is negatively correlated with the long position.

¹²Note that the cumulative trading profit process $V(t)$ is currency denominated and is neither a cumulative excess return nor a cumulative residual with respect to an equilibrium model, since no such model is defined, or needed.

Definition 2 A statistical arbitrage is a zero initial cost, self-financing trading strategy $(x(t) : t \geq 0)$ with cumulative discounted value $v(t)$ such that:¹³

1. $v(0) = 0$
2. $\lim_{t \rightarrow \infty} E^P[v(t)] > 0$
3. $\lim_{t \rightarrow \infty} P(v(t) < 0) = 0$, and
4. $\lim_{t \rightarrow \infty} \frac{Var^P[v(t)]}{t} = 0$ if $P(v(t) < 0) > 0 \quad \forall t < \infty$

Therefore, by definition, a SA satisfies four conditions: (i) it is a zero initial cost, self-financing trading strategy, that in the limit has: (ii) positive expected discounted profits (i.e. investors are required to earn at least the risk free rate on their trading strategy), (iii) a probability of a loss converging to zero, a condition that ensures statistical arbitrage converges to arbitrage, and (iv) a *time averaged* variance converging to zero when the probability of a loss does not become zero in a finite amount of time.¹⁴ This is consistent with the variance of the trading strategy increasing towards infinity with time, but with a “growth rate” less than linear. Condition 4 is essential to generate statistical arbitrage, and addresses the issues discussed in Section 4.2 regarding the limits of arbitrage. In economic terms it implies that a SAO eventually produces riskless *incremental* profit with an associated Sharpe ratio increasing monotonically through time,¹⁵ which thing is

¹³The “if” statement in the fourth axiom is a technical condition and may be ignored when evaluating persistent anomalies. Otherwise, if $P(v(T) < 0) = 0$ for some time $T < \infty$, then a standard arbitrage opportunity is available and the variance condition does not apply, as investors are only concerned with variance when there always exists a positive probability of losing money.

¹⁴A standard arbitrage opportunity can be shown to be a special case of this definition. A standard arbitrage has $V(0) = 0$ where there exists a finite time $T > 0$ such that $V(T)$ satisfies $P(V(T) > 0) > 0$ and $P(V(T) \geq 0) = 1$. To transform the standard arbitrage opportunity into an infinite horizon self-financing trading strategy, we just invest the proceeds at time T into the money market account, i.e. $V(s) = V(T) \frac{B_s}{B_T}$ for $s \geq T$, and $v(s) = V(T) \frac{B_s}{B_T} \frac{1}{B_s} = v(T)$. Then, $\lim_{s \rightarrow \infty} E^P[v(s)] = E^P[v(T)] > 0$ which satisfies condition 2 and $\lim_{s \rightarrow \infty} P(v(s) < 0) = P(v(T) < 0) = 0$ which satisfies condition 3 and implies that condition 4 is not applicable.

¹⁵The time-averaged volatility of the discounted cumulative profit series essentially drops if incremental profits do not contribute to risk as time passes.

inconsistent with well functioning financial markets. Indeed, statistical arbitrage rejects the market as being in any economic equilibrium, an important prerequisite for an efficient market (see Jarrow (1988), chapter 19).

It is important to emphasize that investors need not wait until infinity to benefit from a statistical arbitrage. Those with finite but “long” time horizons would view opportunities that offer positive expected discounted profit, variance (per unit time) that becomes arbitrarily small, and decreasing risk of loss, as “too good to miss” (as are the “approximate investment opportunities” and “good deals” discussed in Section 4.5). To be more precise, although statistical arbitrage is defined over an infinite time horizon, there is a finite time-point such that “pure” arbitrage and statistical arbitrage opportunities are separated by an arbitrarily small loss probability.

Empirical investigations of whether long term trading strategies can be classified as statistical arbitrages basically amount to whether the trading profits processes of such strategies satisfy the four axioms in Definition 2 under an assumed trading profit process.

4.7 Signaling Theory and Implications for Dividend Announcements

4.7.1 Empirical Evidence

Our investigation of the profitability of trading strategies based on dividend announcements is related to the predictions of the signaling theory of dividends, which generally argues that there exists an informational asymmetry between managers (insiders) and shareholders (outsiders) regarding the firm’s future prospects. In the presence of asymmetric information, dividends may be used as a signaling device by managers to communicate to the market their assessment of the firm’s current performance and future prospects. Bhattacharya (1979), Miller and Rock (1985), John and Williams (1985) at-

tempt to explain how and why dividend changes signal information to the market. In general, dividend models posit that dividend announcements transmit information about the firm's future and/or current earnings (prospects of the company) and consequently the changes in the value of the firm around dividend announcements should be proportionate to the changes in dividend policy. Therefore, when a firm unexpectedly increases (decreases) dividends, it signals managements' future optimistic (pessimistic) outlook.

Two important implications of the information-signaling hypothesis have been extensively tested in the literature. The first implication is that dividend changes should be positively associated with subsequent earnings changes. The overall accumulated evidence (Watts (1973), Gonedes (1978), Benartzi et al. (1997)) grants only weak support to the assertion that dividend changes convey information about future changes in earnings, unless extreme dividend changes are considered (Healy and Palepu, (1988), Benartzi et al. (1997)). In fact, Healy and Palepu, using a sample of 131 dividend-initiating firms and 172 dividend-omitting firms over an eleven year period, report a substantial increase in earnings for the initiating firms in the two years after initiation, consistent with signaling; however, for the sample of dividend omissions they conclude that the earnings decline experienced by these firms before and after the omission announcement appeared to be temporary, and was reversed in subsequent years. Benartzi et al. confirm the results of Healy and Palepu using the larger sample of firms and events of Michaely et al. (1995).

The second implication is that unexpected dividend changes should be positively associated with stock price changes.¹⁶ There is a substantial amount of empirical evidence that documents a positive association between dividend changes and excess returns on the announcement day (see, for instance, Pettit (1972), Asquith and Mullins (1983), Aharony

¹⁶Note that a positive association between announcement of dividend changes and stock price movements is also consistent with the free cash flow/overinvestment explanation of why firms pay dividends (Jensen, 1986). A firm with substantial free cash flow will have a tendency to overinvest by accepting investment projects with negative NPV. If managers are overinvesting an increase in dividends will, other things equal, reduce the extent of overinvestment and increase the market value of the firm; a decrease in dividends will have the opposite results. This hypothesis was empirically tested by Lang and Litzenberger (1989).

and Swary (1980), Brickley (1983), Kalay and Loewenstein (1985), Michaely et al. (1995)). Additionally, and particularly in the context of the UK, Lonie et al. (1996) find that for a sample of 620 companies between January to June 1991, dividend increases (decreases) tend to be associated with positive (negative) abnormal returns around the time of the dividend announcement. They note, however, that identifying a unique dividend information effect is particularly difficult in the UK because UK dividends are almost invariably announced simultaneously with earnings. Moreover, Balachandran et al. (1996) document a negative price reaction to a sample of 234 interim dividend cuts or omissions, consistent with signaling theories/information content of dividends. The price reaction is stronger (i.e. more negative) on average where the interim cut/omission occurs for firms that have not reduced their dividends in the previous three-year period. It should also be noted that the available empirical evidence also indicates that unfavorable dividend changes elicit market reactions that are greater in magnitude than favorable dividend changes (De Angelo et al. (1990, 1992, 1996), Healy and Palepu (1988), Michaely et al. (1995)), which thing cannot be explained by the intensity of the news (i.e. the magnitude of the dividend change) or the stocks' liquidity. In a more recent study, Grullon et al. (2002) show that dividend increases are followed by price increases, because they signal that firms enter the maturity stage of the business cycle, and therefore their risk is decreasing.

4.7.2 Post-Announcement Long-Term Abnormal Returns

The conclusion that one can draw from the above discussion is that the prediction of the signaling hypothesis regarding the information content of dividend changes for future earnings is not empirically verified, unless for extreme cases (and then again, only for initiations). On the contrary, the assertion regarding share price reactions to dividend changes is largely supported by empirical studies, albeit in the short-term; for few papers

have dealt with the long-term post dividend announcement price performance. Some early attempts include Charest (1978) who studied price reactions to changes in dividend payout of 10 per cent or more. Using monthly data from 1947 to 1968, Charest finds positive excess returns in the months following dividend increase announcements and negative excess returns following announcements of dividend cuts. Christie (1990) reports one analysis for omitting firms that shows negative returns relative to a size-matched dividend-paying portfolio. More recently, Michaely et al. (1995) investigate the longer term return behavior associated with initiations and omissions of cash dividends, which, being “extreme” events, are signals of a visible and qualitative change in corporate policy. The underlying hypotheses they test when assessing long run performance are generated in terms of underreaction (Michaely et al. draw on the “post-earnings announcement drift” literature to motivate such an underreaction hypothesis) and overreaction (see, for example, De Bondt and Thaler (1985, 1987)). Bernard and Thomas (1989, 1990), among others, find that when firms make surprise earnings announcements, prices continue to drift in the same direction for the next three quarters, which can be interpreted as a type of underreaction. Dividend initiations and omissions, being similar to earnings surprises, might be followed by a similar drift in prices following the change in policy, with the prices of omitting firms drifting down and those of initiating firms drifting up. The overreaction literature would predict exactly the opposite pattern, with the prices of firms which omit dividends displaying positive (mean reverting) excess returns in the period following the omission, since firms that take this action are likely to have been long-term losers.¹⁷ Michaely et al. employ a sample of 561 cash dividend initiation events and 887 cash dividend omission events (NYSE/AMEX companies) widely spread over the period 1964 to 1988, to find evidence in favor of the underreaction hypothesis. Namely, the

¹⁷Overreaction and underreaction phenomena are rationalized by behavioral models such as those developed by Daniel et al. (1998), Barberis et al. (1998) and Hong and Stein (1999). These studies attribute the observed anomalies to irrational investors who suffer from cognitive biases, and conclude that market anomalies provide clear evidence against the Efficient Market Hypothesis.

average excess returns from a buy-and-hold strategy average +7.5 per cent relative to the equally-weighted market index in the first year after the initiation announcement, while the three-year excess return is +24.8 percent. For the omitting firms the first year excess return is -11.0 per cent, reaching -15.3 per cent after three years.¹⁸ However, the long-term results of the omission sample are more robust than those of the initiation sample, being quite pervasive regardless of the benchmark portfolio used. In fact, the (negative) excess returns for the omission sample are more pronounced when using the size-adjusted, beta-adjusted, and industry-and-size adjusted benchmarks, whereas the (positive) excess returns to the initiation sample are reduced considerably for the beta- and size-adjusted benchmarks (the three-year return is about halved), while becoming insignificant (but still positive) for the industry- and size-matched benchmark.¹⁹ Michaely et al. also find that the post-dividend initiation/omission price drift is distinct from and more pronounced than that following earnings surprises.

What's more to the purpose, as a test of the robustness of the results, the authors calculate returns to a theoretically self-financing trading rule employing both samples. For each initiation event, they buy a given equal-dollar long position in the stock at the closing price on the day after the initiation announcement, and offset this position by selling short the equally weighted CRSP index. Similarly, for every omission event, they sell the stock short at the closing price the day after the announcement, and buy an offsetting long position in the equally weighted index. Both positions are held for one year and are subsequently closed out. The average return of the strategy across all years is +9.7 per cent (as a percentage of the long position), with negative returns in only three out of the 25 years. Although excess returns are not concentrated in any one time period,

¹⁸Excess returns for both initiations and omissions are strongly significant, with t-statistics based on the cross-sectional variance of excess returns.

¹⁹The reduction in excess returns (in an absolute sense) of the initiation and omission samples between using the equally-weighted CRSP index and the size-adjusted benchmarks stems from the fact that both samples have somewhat higher concentration of small firms than the NYSE/AMEX population, with small stocks generally outperforming large stocks during the sample period.

Michaely et al. make no claim that the strategy represents a real investment opportunity and do not include transaction costs.

Using size-adjusted returns and the same methodology as Michaely et al. (1995), Benartzi et al. (1997) fail to uncover similar evidence with regards to dividend decreases, while their results for increases are less pronounced than those of Michaely et al. For dividend decreases, they find no significant excess returns for up to three years after the announcement, while for dividend-increasing firms they observe a small, but significant, positive drift. Of course, it should be noted that the sample of Benartzi et al. (1997) excludes dividend initiations and omissions, which are the sole subject of inquiry of the Michaely et al. study, thus dealing with much less “dramatic” events which are expected to generate anyway smaller price reactions.

The real contention to the Michaely et al. (1995) study comes from the work of Boehme and Sorescu (2002), who argue that the results of the former authors lack methodological and intertemporal robustness. Boehme and Sorescu draw on the debate surrounding the existence of long-term abnormal stock returns, particularly following corporate events. The first leg of this debate concentrates on the biasedness and vulnerability of long-term abnormal return measures to incorrect specification of market equilibrium models (Fama (1998), Mitchell and Stafford (2000)). In particular, Mitchell and Stafford (2000) argue that, unlike calendar-time methodologies, the buy-and-hold methodology exacerbates the misspecified model problem. Since the true asset pricing model is not known, any potentially spurious “abnormal” return occurring at the beginning of the post-event period would be compounded over longer horizons. A common method of addressing uncertainty over the measure of expected returns is to examine the robustness of the results to alternative measures, as indeed carried out in Michaely et al. with the use of different benchmarks. Perhaps a superior methodology for addressing risk measurement is the use of zero-investment portfolios, as in Boehme and Sorescu, and Eberhart et al. (2003). These

portfolios appeal to the matched firm method of controlling for risk, while also incorporating the advantages of the calendar-time factor models. They consist of long positions in the sample firm stocks and short positions in their matched firm stocks (matched based on characteristics such as prior-event momentum, size, and book-to-market). The zero investment portfolio returns are then adjusted for risk again using a factor model such as the three-factor model of Fama and French (1993). Any remaining residual return is deemed to be “abnormal”.

The second leg of the debate revolves around statistical matters and is independent of the method of estimating expected returns. Fama (1998) and Mitchell and Stafford (2000) argue that event-time returns are an inappropriate metric for computing long-term returns. Boehme and Sorescu criticize the buy-and-hold methodology (and the closely related cumulative abnormal return metric) as being particularly vulnerable to the problem of cross-sectional dependence among event firms in nonrandom samples, due to calendar time clustering and substantial overlapping of the postannouncement horizons, which is likely to yield overstated t-statistics (Mitchell and Stafford (2000)).²⁰ This is of paramount concern in the study of Boehme and Sorescu which covers a large number (2,800) of dividend initiations and resumption events (which they argue are similar in nature to dividend initiations) over the period 1927 to 1998. Also, buy-and-hold abnormal returns usually suffer from severe skewness which leads to misspecified statistics (though this particular problem can be addressed using bootstrap methods as in Lyon et al. (1999)). On the contrary, Barber and Lyon (1997) show that the arithmetic summation of returns (as is done with calendar-time returns) does not precisely measure investor experience, and Lyon et al. (1999) demonstrate that the calendar-time method is generally misspecified in

²⁰Note that Michaely et al (1995) demonstrate an awareness for this problem in a footnote, however, they mention that for their sample it's not a serious consideration. The extent to which the two samples (initiations and omissions) overlap is small, with events well spread over the 25 year sample period; only about 5 (15) per cent of the observations partially overlap in one-year (three-year) excess returns calculations. Also, they estimate and correct for the (small) correlation in excess returns, with negligible effect on the results.

nonrandom samples. Moreover, Loughran and Ritter (2000) argue that the calendar-time return metric has low power.

Boehme and Sorescu (2002), though admitting that buy-and-hold returns are arguably more representative of the overall investment experience, resort to the calendar time methodology which involves calculation of standard errors based on the time series portfolio variance, in which the cross-correlations of event-firm abnormal returns are automatically accounted for.²¹ Carrying out regressions of calendar time portfolio returns on the Fama-French factors, they reveal positive abnormal performance for the combined sample of initiations and resumptions of NYSE/AMEX/NASDAQ firms over 1927 to 1998 *only* for the equally weighted portfolio (reaching 12 per cent in the three-year post-announcement period).²² On the contrary, the value weighted results are weakly positive and statistically insignificant, suggesting that the price drift is confined to the smaller firms in the sample.²³ Actually, excluding the largest decile firms from the sample renders the value-weighted results significant for the remaining 90 per cent of firms. This likely explains why equally weighted abnormal returns for the whole sample of firms are statistically significant while the corresponding value-weighted results are not. Although the price drift is likely to be of limited macroeconomic significance, from the perspective of a money manager, it raises the question of whether a profitable trading rule could be implemented involving purchases of equities in the lowest nine deciles (which, while accounting for only 12 percent of the US market capitalization, they were nevertheless

²¹Calendar time portfolios are constructed as follows: for each calendar month, the monthly return to both equally weighted and value weighted portfolios of firms that have been subject to dividend events during the $[c-h, c-1]$ prior period is calculated, where c is the calendar month and h is the investment horizon of interest. The portfolios are rebalanced each month to reflect the changing portfolio composition.

²²Of course, note that their findings throughout are predicated on the validity of the three factor Fama-French equilibrium model.

²³For comparison, the buy-and-hold (and cumulative) abnormal post-event returns are provided, and are in conflict with the calendar portfolio results since both equal- and value-weighted long-term abnormal returns are significant. Boehme and Sorescu (2002) interpret this evidence as reiterating Mitchell and Stafford's arguments that buy-and-hold abnormal returns tend to magnify spurious abnormal performance induced by potentially misspecified asset pricing models. Note, however, the objections to the calendar time method of Barber and Lyon (1997), Lyon et al. (1999) and Loughran and Ritter (2000).

worth an aggregate of \$1.9 trillion at the end of 1998).

Boehme and Sorescu argue against profitable exploitation of the observed price drift by rationalizing it via a postannouncement decline in the loadings of the three Fama-French factors, which thing occurs *independently* of the dividend event.²⁴ Of course, behaviorists would argue that abnormal returns may arise because investors suffer from cognitive biases and are slow to update their prior beliefs regarding postdividend changes in risk and profitability. On the other hand, the positive price drift may just be a product of *chance*, fully consistent with rational behavior: If the sample is overpopulated with firms that become unexpectedly less risky or more profitable, stock prices will increase after the dividend announcement, reflecting investors' rational reaction to the discovery of unexpected information. The authors favor the second explanation, which is consistent with the EMH, particularly since the observed price drift is shown to lack robustness across firm sizes and time periods. No significant abnormal performance for either initiations, resumptions, or the combined sample is documented for the period 1927 to 1963, for either equal- or value-weighted portfolios. Thus, the authors argue, abnormal returns are not robust across time, and when they do exist, they are confined to small stocks.

It is evident from the previous discussion that the literature has not settled on whether a long-term, pervasive, "dividend announcement anomaly" actually exists in the first place, particularly with regards to dividend initiations. A good way of assessing the robustness of the anomaly is to examine the long-term price/return performance following dividend announcements in countries other than the US, and compare results with US findings. Particularly interesting are the contentions of Michaely et al. (1995) and Boehme and Sorescu (2002) that trading strategies involving dividend omitting and dividend initiating firms might yield excess returns. Motivated by the aforementioned studies

²⁴A decrease in risk factor loadings might represent an unpredicted decrease in the cost of equity (discount rate) that is unrelated to dividends and is not fully incorporated in prices on the announcement day. Alternatively, firms experiencing a decline in the loadings of the size and book-to-market factors will simultaneously experience positive abnormal returns due to a period of unexpectedly stronger cash flows (Fama and French (1997)).

and their findings, we construct trading strategies in the spirit of Michaely et al. using dividend announcements of UK firms, and evaluate their profitability in a costly trading environment.

4.8 Empirical Methodology

4.8.1 The Statistical Arbitrage Test

Given Definition 2 in Section 4.6, Hogan et al. (2004) propose a test for SA based upon an assumed process for the evolution of the discounted cumulative trading profits $v(t_1), v(t_2), \dots, v(t_n)$, generated by a zero-cost, self-financing, "long horizon" trading strategy. The differenced terms $\Delta v_i = v(t_i) - v(t_{i-1})$ represent the trading strategy's incremental discounted trading profits measured at equidistant time points $t_i - t_{i-1} = \Delta$, monthly in this case. To test for statistical arbitrage, the authors initially employ a pretty general stochastic process to describe the dynamics of Δv_i , which encompasses linear and potentially quadratic specifications for the evolution of the mean and variance of trading profits, depending on the magnitude of θ and λ .²⁵

$$\Delta v_i = \mu i^\theta + \sigma i^\lambda z_i \quad (4.5)$$

for $i = 1, 2, \dots, n$, where z_i are i.i.d. $N(0, 1)$ random variables, although the assumption of independence is subsequently relaxed. The initial quantities z_0 and Δv_0 are both zero, by definition. The parameters σ and λ determine the volatility of discounted incremental trading profits while parameters μ and θ their expected value:²⁶ It is easy to see that

²⁵This can be justified by a Taylor series expansion of functions i^θ and i^λ , eg. $i^\lambda = 1 + \ln(i)\lambda + \frac{1}{2}(\ln(i))^2\lambda^2$ plus higher order terms, where the convention $\ln(\cdot)$ is used to scale the increasingly large values of the time index.

²⁶Another example of a possible process is $\Delta v_i = \mu e^{i\theta} + \sigma e^{i\lambda} z_i$, which exhibits rapid (exponential) changes in the mean and variance of trading profits as compared to the gradual evolution of expression (4.5). For $\lambda < 0$, such a process leads to "faster" acceptance of statistical arbitrage as compared to the process in (4.5), which is preferable if one wants to have a more stringent test for statistical arbitrage.

$E[\Delta v_i] = \mu i^\theta$ and $var[\Delta v_i] = \sigma^2 i^{2\lambda}$. For $\lambda < 0$, the variance of Δv_i decreases over time, which ultimately satisfies the fourth condition of statistical arbitrage, as proved by Hogan et al. Note that expression (4.5) with $\mu > 0$ and $\lambda < 0$ does not imply that one should wait for the volatility to decline before investing. Instead, it is optimal for investors faced with such an opportunity to immediately begin trading and earn a positive expected profit while enjoying the benefit of decreasing time-averaged variance.

The use of normal increments in (4.5) may be justified by the Central Limit Theorem. The discounted cumulative trading profit $v(t)$ is, by definition, the sum of the Δv_i 's, and a normalized sum of increments results in an asymptotically normal random variable, often with rapid convergence, under mild regularity conditions (mainly uniform asymptotic negligibility or finite second moment (see Resnick, Chapter 9, page 315, the Lindeberg-Feller Central Limit Theorem and Lindeberg condition)). Moreover, in theory, discounted trading profits derived from portfolios are well represented by a normal distribution since the impact of idiosyncratic jumps is mitigated.

Given the process in expression (4.5), the discounted cumulative trading profits generated by the trading strategy are

$$v(t_n) = \sum_{i=1}^n \Delta v_i = \mu \sum_{i=1}^n i^\theta + \sigma \sum_{i=1}^n i^\lambda z_i \stackrel{d}{\sim} N \left(\mu \sum_{i=1}^n i^\theta, \sigma^2 \sum_{i=1}^n i^{2\lambda} \right) \quad (4.6)$$

Parameters μ, λ, σ , and θ can be obtained by maximum likelihood estimation of the log likelihood function of the increments in equation (4.5). A trading strategy satisfies the definition of a statistical arbitrage with $1 - \alpha$ percent confidence if the following conditions hold jointly:

1. $H1 : \mu > 0$
2. $H2 : \lambda < 0$

$$3. H3 : \theta > \max \left\{ \lambda - \frac{1}{2}, -1 \right\}^{27}$$

with the sum of the p values for the individual tests forming an upper bound for the Type I error α .

The first sub-hypothesis tests for positive expected profits and is a consequence of the second condition for statistical arbitrage (note that any value of θ ensures that $\mu \sum_{i=1}^n i^\theta > 0$ provided $\mu > 0$). The second sub-hypothesis implies the trading strategy's time-averaged variance declines over time: λ must be negative to ensure $\frac{Var[v(n)]}{n} = \frac{\sigma^2 \sum_{i=1}^n i^{2\lambda}}{n} \rightarrow 0$, so that the fourth condition of statistical arbitrage is satisfied. Economically, the third sub-hypothesis tests for "long run" market efficiency: By involving both the trend in expected profits as well as volatility, it ensures that a potential decline in expected trading profits is not occurring at a "negative enough" rate to prevent convergence to arbitrage, so that the probability of a loss converges to zero as required by the third condition. For a proof of H3 see Theorem 1 in Hogan et al.

The three sub-hypotheses are tested individually using the Bonferroni inequality for multiple hypotheses which stipulates that the sum of the p -values for the individual tests becomes an upper bound for the Type I error of the joint hypothesis test.²⁸ Standard errors for the hypothesis tests in conditions 1-3 are extracted from the Hessian matrix to produce t -statistics and their corresponding p -values.²⁹

The model described in equation (4.5) represents the Unconstrained Mean (UM) model which allows for time-varying expected profits. Following Hogan et al. (2004), we consider as well a more restrictive Constrained Mean (CM) model that assumes constant expected trading profits by setting θ equal to zero. Consequently, the CM version of statistical

²⁷The third hypothesis $\theta > \max \left\{ \lambda - \frac{1}{2}, -1 \right\}$ actually contains two hypotheses but the second component $\theta > -1$ is a technicality (see Theorem 1 of Hogan et al.) while the remaining three conditions have economic interpretations.

²⁸ $P(\cup_{i=1}^n H_i) \leq \sum_{i=1}^n P(H_i)$

²⁹The gradient functions used in the estimation of the parameters and the analytic Hessian matrix can be obtained from the author upon request.

arbitrage has incremental trading profits evolving as

$$\Delta v_i = \mu + \sigma i^\lambda z_i \quad (4.7)$$

For the CM version of SA in equation (4.7), sub-hypothesis H3 of the SA test is eliminated.

Finally, it should be noted that since the test for statistical arbitrage is performed conditional on the process in (4.5) or (4.7) for Δv_i , Hogan et al. (2004) gauge the robustness of the assumed process via extensive simulations to investigate the impact of jumps and nonstationary parameters on inferences regarding the presence of SA. The power of the test proves to be exceptional even with deviations from the assumed process. If anything, the simulations imply that the above mentioned deviations lead to a bias towards accepting the null hypothesis of no SA and thus market efficiency. Hence, the formulation in expressions (4.5) and (4.7) may be considered “fail-safe” in the presence of deviations.³⁰

4.8.2 Correlated Incremental Trading Profits

Finally, we address the issue of serial correlation in incremental trading profits which is likely to arise from the overlapping nature of the monthly holding periods (as is usual in financial anomaly portfolios) by modifying the innovations of equations (4.5) and (4.7) to follow a MA(1) process given by

$$z_i = \varepsilon_i + \phi \varepsilon_{i-1} \quad (4.8)$$

where ε_i are i.i.d. $N(0,1)$ random variables. As proved in Hogan et al. (2004), the presence of an MA(1) process does not alter the conditions for SA, nor increase the number of sub-hypotheses. Although they do not account for autocorrelation explicitly,

³⁰This result stems from the fourth property of statistical arbitrage. The additional volatility caused by jumps and non stationary parameters increases the standard error of λ , which translates into higher corresponding values for $H2$, and thus a higher probability of accepting the null hypothesis of no SA.

their simulation tests indicate that in the presence of serial correlation the power of the SA test is exceptional. However, including the additional parameter ϕ may improve the statistical efficiency of the remaining parameter estimates and avoid inappropriate standard errors. In the empirical analysis that follows, the UM and CM models are estimated jointly with equation (4.8).

4.8.3 Probability of Loss

An additional advantage of the SA methodology over traditional market anomaly tests is its ability to yield the probability of loss at specific time horizons. Shleifer and Vishny (1997) demonstrate the importance of capital constraints and intermediate losses to trading decisions. These considerations, if valid for the specific investor/trader, do not allow all SA opportunities to be equally desirable. Instead, the convergence rates of the loss probabilities to zero offer guidance regarding which strategies to pursue.

The probability of a trading strategy generating a loss after n periods, the subject of axiom 3 in Definition 1, depends upon the model parameters and is estimated as

$$\Pr\{Loss\ after\ n\ periods\} = \Phi\left(\frac{-\mu \sum_{i=1}^n i^{\theta}}{\sigma(1+\phi)\sqrt{\sum_{i=1}^n i^{2\lambda}}}\right) \quad (4.9)$$

where $\Phi(.)$ is the cumulative standard normal distribution function. This probability converges to zero at a rate faster than exponential as shown in Hogan et al. Note that although the MA(1) parameter ϕ does not alter the SA conditions, it influences directly the convergence rate to arbitrage. Finally, the UM trading profit process includes all five parameters in equation (4.9) while the corresponding loss probability for the CM model has θ set equal to zero.

4.9 Data

The data employed are primarily derived from the 2002 London Share Price Database (LSPD), which contains a complete price history of all UK companies quoted in London since 1975, including companies that subsequently failed, merged or de-listed. Once the dividend initiations and omission events had been identified, they were verified, where possible, from individual company accounts held on Datastream. In addition, dividend announcement dates provided by the LSPD database were double-checked, where possible, from the Annual Financial News Summary published by Extel Financial Ltd, and a small number of discrepancies (nine) was found and corrected.

Our dataset consists of all London quoted non-financial companies and covers the period from March 1984 to May 2002 for the initiations sample, and June 1992 to May 2002 for the omissions sample.³¹ In the UK, firms generally declare two dividends during any one fiscal year - an interim dividend after six months of the accounting year and a final dividend at the end of the accounting period. Following Michaely et al. (1995) and Boehme and Sorescu (2002), we define a dividend initiation event as the first cash dividend payment in the history of a firm. Potential dividend initiation candidates included firms first quoted in SEDOL at the same time or after entering the LSPD database. We excluded companies with a SEDOL birth date earlier than when data first started being available (either in the LSPD or Datastream), to avoid the case of a company paying dividends before we have records for it. Of course, we also excluded companies whose first announcement date was missing. In addition, we examine dividend initiations together with dividend resumptions, as in Boehme and Sorescu (2002), who note that these events are likely to have economic significance similar to dividend initiations. We define a dividend resumption as the first cash dividend paid by a firm following a hiatus in payments

³¹Dividend announcement dates were missing from the LSPD for the vast majority of firms between 1977 and 1984. For dividend omitting firms, we had to restrict the sample even further as dividend announcement dates were not available regularly prior to 1992.

for at least 12 months. Our combined initiations and resumptions sample finally consists of 967 initiations and 235 resumptions, widely spaced over our sample period.

For a company's dividend record to be considered as a potential omission event in our sample, one of the following must have occurred:

(1) The company declared at least three consecutive semi-annual cash payments and then paid no cash payments in the next six months.

(2) The company declared at least two consecutive annual cash payments and then made no cash payment in the following year.³²

Excluding firms that did not actually omit a cash dividend but changed to another type of cash payout such as return-of-capital payments, bonus and special dividends (12 exclusions), we arrive at a "clean" sample of 447 cash dividend omission events.

Monthly equity price data for the dividend initiating/resuming and dividend omitting firms as at the end of the announcement month and for up to 24 months after are obtained and used to calculate returns for some fixed horizons (see Section 4.10). Although in long-term event studies it is important for the experiment to begin on the exact date of the announcement and daily returns are thus employed, in testing for SA it is pertinent that the equity portfolio is formed at a fixed point in time. Moreover, Canina et al. (1998) show that compounding daily returns over long horizons induces significant upward biases in long-term returns for the equal-weighted index, partly due to daily autocorrelations and bid-ask bounces, and suggest using the monthly index instead of the daily.

An investment of £1 is maintained in the portfolios at all times. The self-financing condition is enforced by investing (borrowing) trading profits (losses) generated by various trading strategies in the riskfree asset. The riskfree data used is the 1-month Treasury Bill from the LSPD Database.

³²Michaely et al. (1985) use similar criteria to identify omission events.

4.10 Dividend Announcement Trading Strategies

The trading strategies that we employ are in the spirit of Michaely et al. (1995). We use end of month share prices for the individual stocks and the FTSE All Share Index, and group stocks according to the announcement month. At the end of the month, we initiate a short position in the portfolio consisting of the stocks that have omitted a dividend in the particular month, and match this by a long position in the index. This procedure is repeated for each month throughout the sample. On the contrary, each month we initiate a long position in portfolios of dividend initiating/resuming stocks and “matching” short positions in the FTSE All Share Index.³³ In the long stock portfolio case, dividends paid after portfolio formation are added in the month on which the stock goes ex-dividend.

These zero-investment (semi-hedged) positions are held for 3, 6, 12, 18, and 24 months respectively.³⁴ The portfolios are rebalanced monthly to account for stocks that drop out of the database during the holding period. We consider both equal-weighted and value-weighted stock portfolios, where for value weighting we employ the market values in the month prior to the announcement month, as in Boehme and Sorescu (2002). The latter authors have shown that the positive price drift experienced by firms that initiate or resume dividends becomes generally insignificant when portfolios are value-weighted, indicating that the price drift is confined to small firms. All in all, we examine 10 trading strategies (5 equal- and 5 value-weighted) involving dividend initiating/resuming firms and 10 strategies involving dividend omitting firms.

³³We could have also used other benchmark indices such as the FTSE 100 and the FTSE350. However, doing so might expose our results to data snooping criticisms. We have settled on the FTSE All Share Index as the most appropriate characterization of the market

³⁴Note that the momentum literature uses holding periods of up to 12 months, while the earnings and dividend literatures also consider longer horizons. Our choice of investment horizons is consistent with Michaely et al. (1995) and Benartzi et al. (1997).

4.10.1 Transaction costs

A common critique of financial anomalies is that the trading profits from such anomalies disappear after adjusting for transaction costs. Therefore, the portfolio returns from long and short positions are adjusted for the influence of transaction costs before testing them for SA. As in Hogan et al. (2004), we first estimate the average monthly turnover for each of the portfolios by taking a ratio of the sum of buys and sells each period over two times the total number of stocks held in that period. The resulting number is an estimate of the average round trip transactions as a percentage of the number of stocks held. This measure of monthly turnover is then multiplied with 2.1%, a “high” estimate of the round trip transaction cost for UK firms³⁵: Gemmill (1998) reports a 39 basis point spread for large UK companies and a 79 basis point spread for small companies before the introduction of the new electronic trading system (SETS) in the London Stock Exchange in October 1997. By contrast, the respective spreads after the introduction of SETS were 32 basis points and 53 basis points. Taylor et al. (2000) largely confirm these estimates. To be conservative about the magnitude of portfolio returns, we employ the 79 basis point estimate for the whole of the sample period, multiply it by two for a round-trip trade, and add the 0.5% stamp duty (on purchases) which was applicable over our sample period.

We adjust the monthly profits downward by the transaction costs and convert them into pound denominated trading profits with gains and losses accruing through time according to the riskfree rate. The statistical arbitrage test described in Section 4.8 is then applied to the incremental (i.e. monthly) trading profit series.

³⁵Pesaran and Timmermann (2000) use a “high” transaction cost scenario where trades in UK shares (one-way) cost one percent.

4.11 Empirical Results

Table 4.1 contains summary statistics for the incremental trading profits of the dividend announcement strategies under investigation. For the omission strategies, results for only the 3 and 6 month holding periods are reported, since the average returns for the longer holding periods are negative, and testing these portfolio returns for statistical arbitrage is meaningless. It is obvious from Table 4.1 that the range of portfolio returns (Max-Min) as well as the standard deviation generally increases with the investment horizon, as expected.

Table 4.2 presents the results for statistical arbitrage under the assumption that expected incremental trading profits are constant over time (the CM model). Two hypotheses are jointly tested. First, the incremental profits from the strategy must be statistically greater than zero ($\mu > 0$), and second, the time-averaged variance of the strategy must decline to zero as time approaches infinity ($\lambda < 0$). T-ratio tests on the expected profits of the portfolios are also presented for comparison.

Beginning with equal-weighted portfolio results (Panel A), it is obvious that the INI portfolios' expected monthly trading profits are large and statistically greater than zero even at the 1 percent level.³⁶ Generally, the estimate of μ increases with the holding period. For all the equal-weighted INI portfolios, the point estimate for the growth rate of the variance (λ) is less than zero and statistically significant, indicating that these strategies become less risky over time.³⁷ In short, all the INI equal-weighted trading strategies converge to riskless arbitrages with decreasing time-averaged variances, generating statistical arbitrage at the 1 percent level (see the H1+H2 column). Parameter ϕ is positive for all INI trading strategies, increasing in magnitude with the holding period (and thus

³⁶Note that the mean incremental profit, μ , is related but not identical to the usual mean returns from the trading strategy since μ is a pound denominated quantity derived from a self-financing trading strategy.

³⁷Note that due to the negative value of λ obtained, the estimates of σ tend to be higher than the unconditional standard deviation of the portfolio returns.

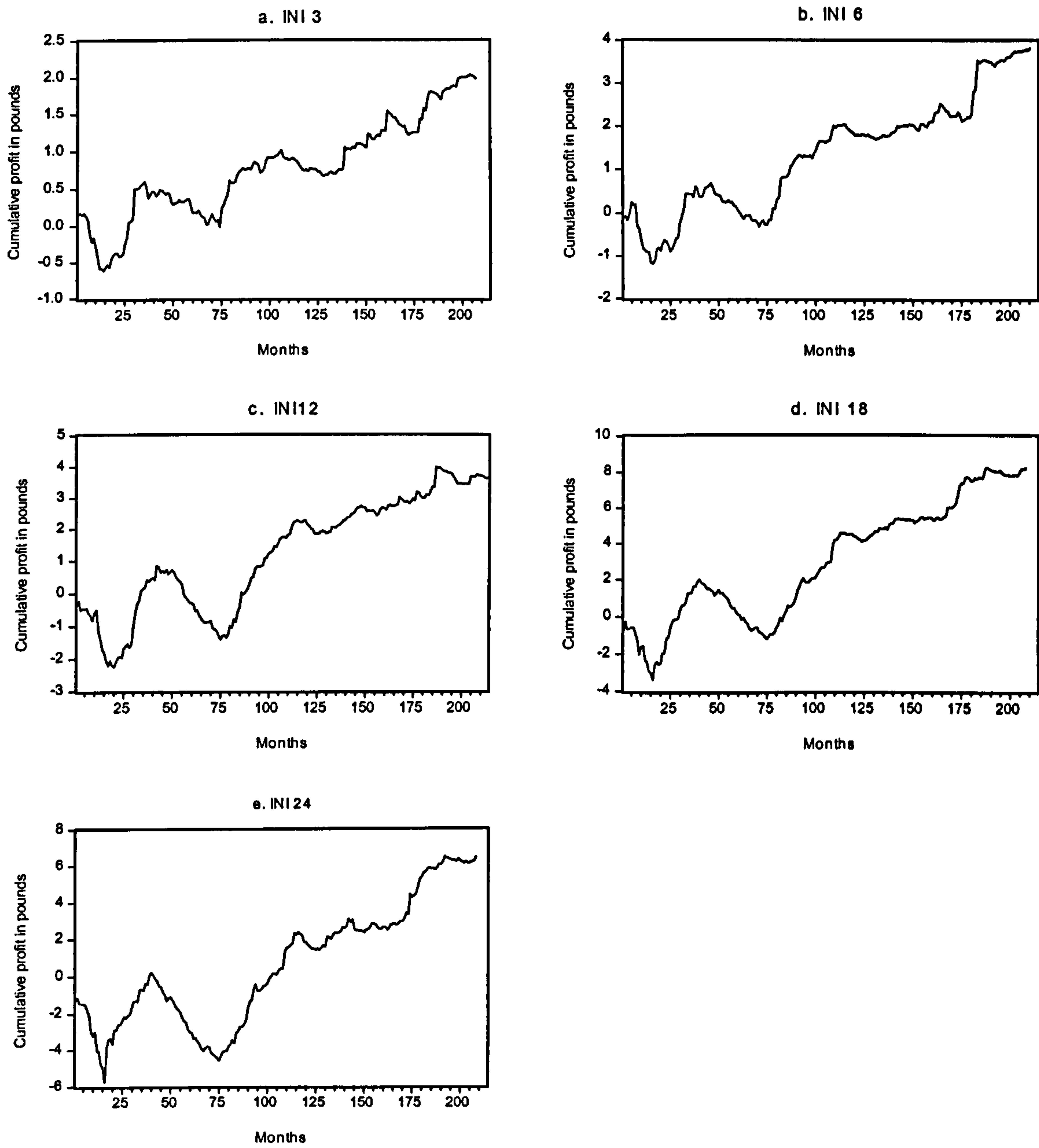
with the degree of overlap), but significant for the 12 month horizon onwards. Though ϕ has no role in the no SA null hypothesis, the influence of its inclusion on the other parameters and their standard errors is unknown apriori, and should be accounted for.

Panel B of Table 4.2 presents the value-weighted results, allowing comparison with the equal-weighted outcomes from Panel A. This exercise is an important robustness check on the results, as it allows us to evaluate whether concluding in favor of SA hinges on the presence of the smaller stocks in the sample.³⁸ Focussing first on the INI strategies, expected monthly trading profits are always smaller than their equal-weighted counterparts, indicating that a “small stock effect” exists in our sample. However, the significance of the μ parameter is only seriously compromised for the 24 month strategy. With variance growth rates statistically less than zero for all value-weighted INI strategies, we can only accept the null of no SA for the INI24 strategy, while INI12 tests positively for SA at the 10 percent level. Therefore, in total, out of the 10 INI strategies examined, 9 are constrained-mean statistical arbitrages at the 10 percent level (8 at the 5 percent level). This finding is hard to reconcile with the notion of market efficiency.

Figures 4.1 and 4.2 below depict the discounted cumulative profit over time of the equal- and value-weighted dividend initiation strategies respectively which test positively for SA with the CM model. In general, profits tend to increase with the investment horizon, which is in line with point estimates of the monthly expected profit μ . However, investors may have to incur losses in the short-term; a trading strategy that yields the highest cumulative profit is not necessarily optimal, particularly if investors are capital-constrained.

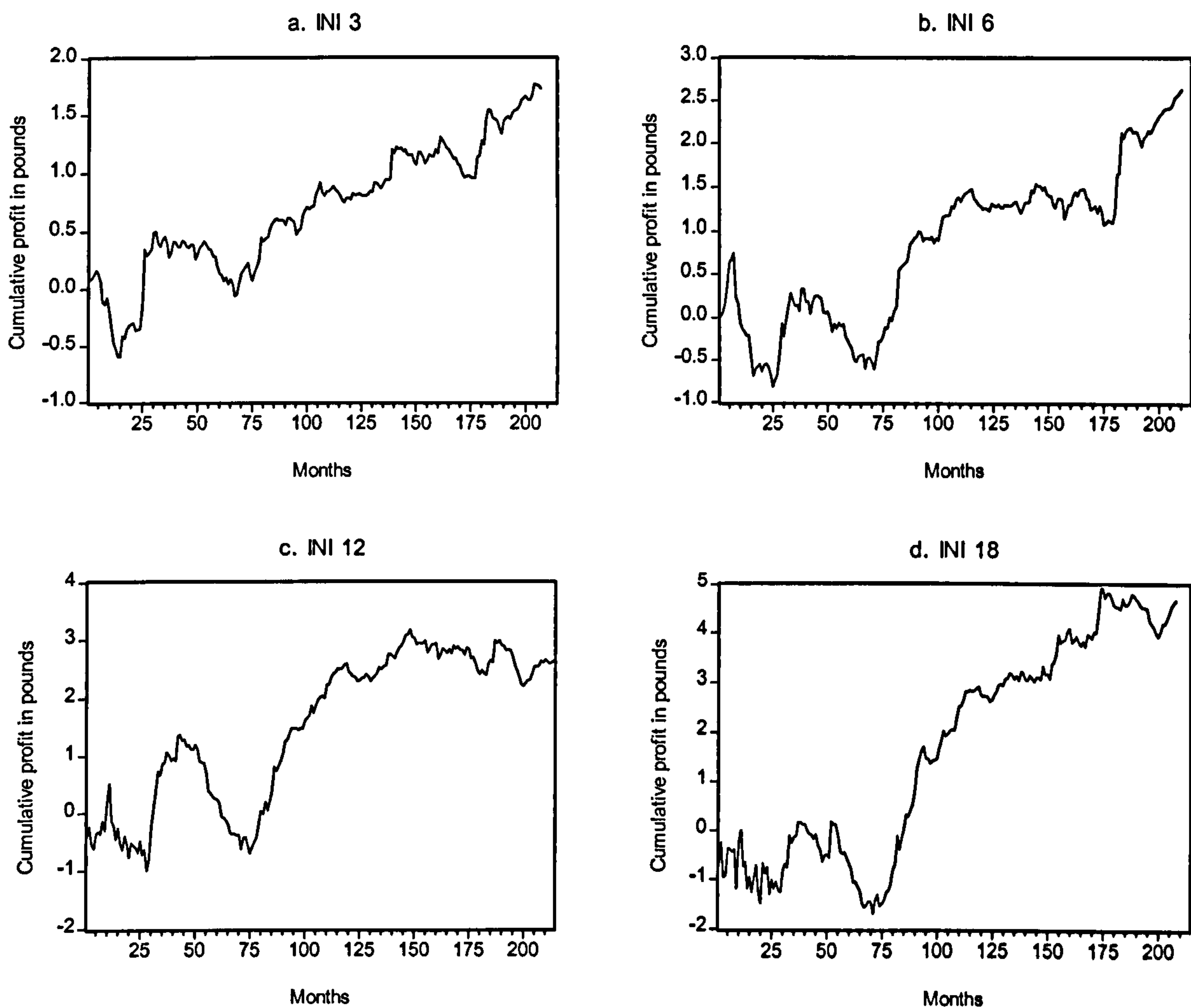
³⁸It is well known that small stocks are less efficient than large stocks (eg. Hong et al. (2000), Mitchell and Stafford (2000)), experiencing larger price drifts.

Figure 4.1



Note: Comparison of the discounted cumulative profits of the equal-weighted dividend Initiation strategies. £1 is invested at all times in all portfolios. Any profits (losses) are re-invested (financed with) the risk free asset

Figure 4.2

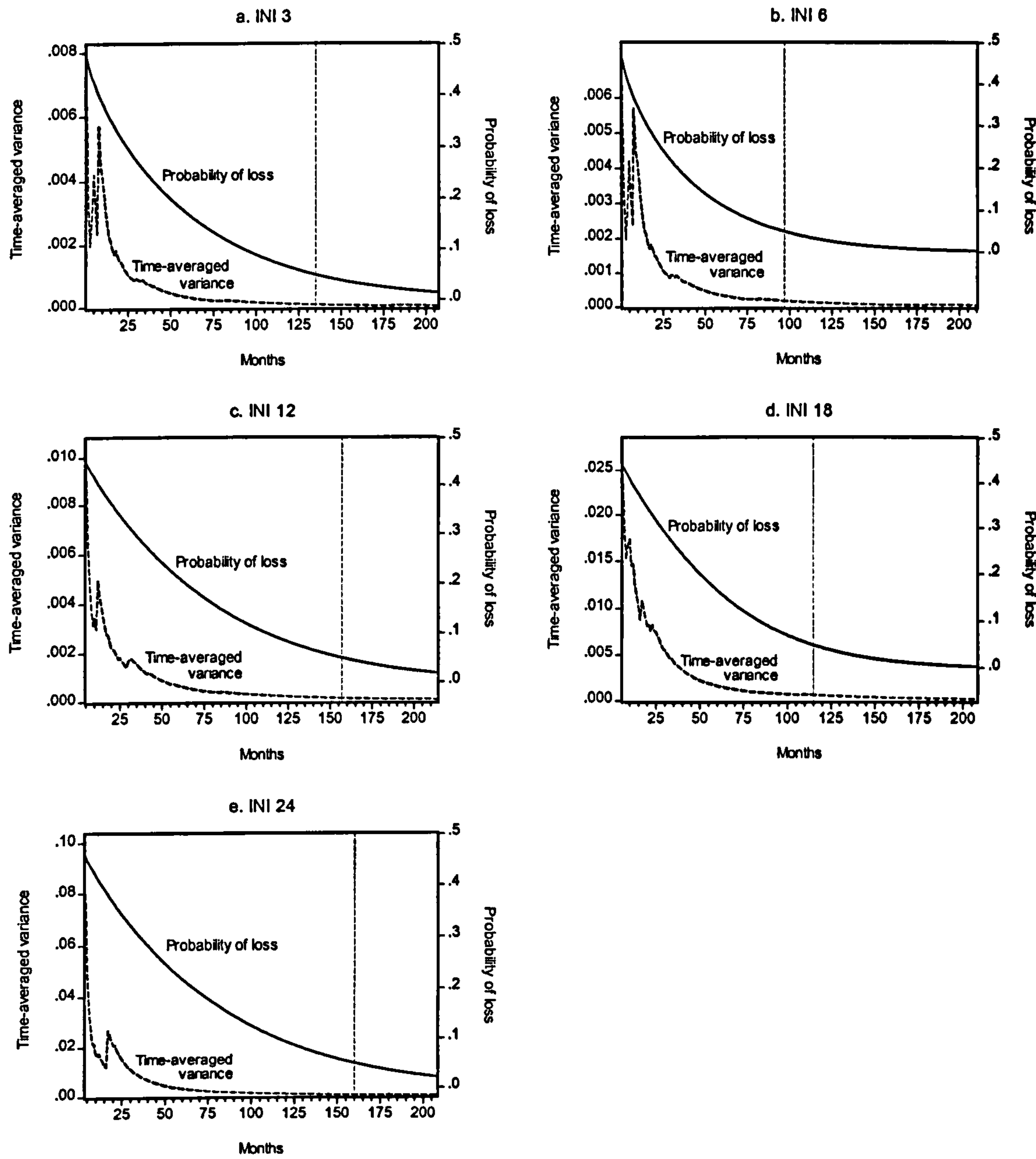


Note: Comparison of the cumulative profits of the value-weighted dividend Initiation strategies. £1 is invested at all times in all portfolios. Any profits (losses) are re-invested (financed with) the risk free asset

To get a sense of how fast the statistical arbitrages are converging to riskless arbitrages, we plot the probability of a loss using equation (4.9), accounting for the effects of the serial correlation parameter ϕ only when it is statistically significant. The time-averaged variances of the strategies are plotted as well. Figures 4.3 and 4.4 below refer to equal- and value-weighted initiation strategies respectively which test positively for SA with the CM model. The vertical dotted line indicates the month at which the probability

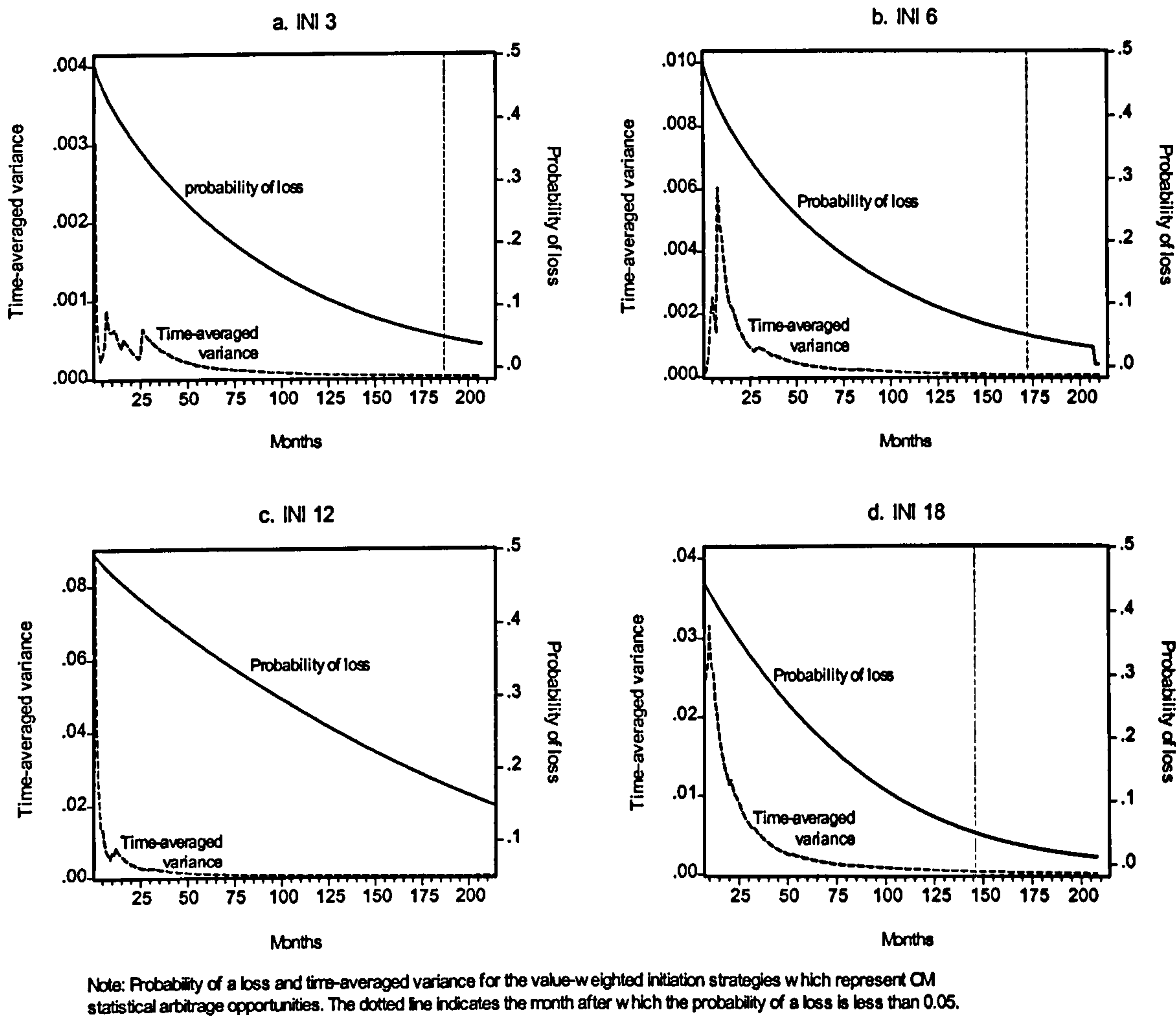
of a loss first drops below 5 percent.

Figure 4.3



Note: Probability of a loss and time-averaged variance for the equal-weighted Initiation strategies which represent CM statistical arbitrage opportunities. The dotted line indicates the month after which the probability of a loss is less that 0.05.

Figure 4.4



A casual observation of the time-averaged variance graphs in Figures 4.3 and 4.4 reveals that both equal- and value-weighted initiation portfolio strategies converge rather rapidly to riskless arbitrages. The time-averaged variance graphs exhibit an erratic pattern in the first few months of trading, but soon attain a smooth, fastly declining trend. In general, the equal-weighted strategies exhibit probabilities of loss reaching the 5 percent threshold faster than corresponding value-weighted results. Note that the INI 12 value-weighted

strategy does not reach a loss probability of even below 10 percent during our sample period. A capital-constrained investor who is worried about “risky” arbitrage may choose to sacrifice the upside potential of some strategies for others with lower intermediate losses and lower probability of loss. For example, the 6-month holding period equal-weighted initiation strategy has a probability of loss falling below 5 percent after just 97 months of trading. This compares with considerably longer trading horizons required by other strategies, which in the long-run appear more profitable.

As mentioned earlier, omission strategies are only examined for statistical arbitrage up to the 6 month holding period, since monthly expected trading profits are negative for longer horizons. This result is in contrast with the findings of Michaely et al. (1985) for the US, which argue in favor of a negative price drift for dividend omitting stocks extending for up to 3 years after the omission announcement date. Our findings indicate that both equal- and value-weighted portfolios do not present SA opportunities at conventional significance levels due to μ being insignificant, even though positive.

We next check whether the estimated CM models which have led us conclude in favor of SA opportunities in the UK market with dividend initiating/resuming stocks offer a good fit for the incremental trading profit process. To this purpose, we also estimate the UM model with MA(1) errors (expressions (4.5) and (4.8)), which is a more general specification of trading profit dynamics, and compare measures of fit for the CM model with those of the UM model. We also study the estimated rates of change in the expected trading profits and implement a likelihood ratio test.

Table 4.3 presents results for both equal- and value-weighted portfolios. In the vast majority of cases, the θ parameter is positive. However, as the information contained in trading profits is spread over a fourth parameter, the point estimate of μ becomes much smaller when compared with the corresponding CM estimates and insignificant. For the two value-weighted INI portfolios which exhibit negative θ parameters, the point estimates

of μ increase along with their standard errors and are again insignificant. In fact, none of the trading strategies test positively for SA with the UM model.³⁹

We test whether the incremental trading profits of the portfolios are increasing/decreasing for positive/negative θ s respectively using a t-statistic, and record the p-values for this test. We find that for all portfolios the growth rate of the incremental profits is statistically indistinguishable from zero. Therefore, there is no need to estimate θ and weaken the power of the test. More formally, we employ a likelihood ratio test for the restriction $\theta = 0$ (see also Hogan et al. (2004)), the values of which are reported in Table 4.3. Comparing results with the $\chi^2_{1,0.10}$ critical value of 2.71 shows that for all trading strategies, the null hypothesis that $\theta = 0$ is accepted without reservation.

The two measures of fit we examine are the average root mean squared error (RMSE) and the sum of normalized squared residuals, i.e. residuals divided by their standard deviation, abbreviated as SSR. For the former measure, 10,000 simulations of incremental trading profit series for each trading strategy are conducted, using the parameter estimates of the observed incremental trading profit process for both the CM and UM models. Each simulated profit series has the same length as the observed sample. The RMSE between the observed trading profits and those from each simulation is computed, and the average is reported in Table 4.3. If the UM model offers a better fit for the data than the CM model, then the RMSE numbers of the former should be lower than those of the latter. There is no consistent evidence across the portfolios in favor of the above notion. In fact, the RMSE numbers for the CM and UM models are very similar for all portfolios, casting doubt on the need to complicate the trading profit process. Finally, the SSR numbers for the two models are again quite close.

Summarizing, the UM model for statistical arbitrage reduces drastically the estimate of the mean incremental profit and/or unnecessarily increases the standard error of μ without offering notable improvements in goodness of fit as compensation. Hence we conclude that

³⁹This is why detailed results on the μ and λ estimates are not reported for the UM model.

the CM model is more appropriate for modeling observed incremental trading profits.⁴⁰

4.12 Conclusion

In this chapter we have carried out an empirical investigation of trading strategies involving announcements of considerable changes in dividend policy in the UK, such as dividend initiations/resumptions and dividend omissions. Such trading strategies have not been examined thoroughly even in a US context. We test the incremental trading profits derived from suitably devised strategies for statistical arbitrage using the methodology of Hogan et al. (2004), which facilitates a test of market efficiency without the need to specify an equilibrium model. In the limit, statistical arbitrage converges to arbitrage. Consequently, the joint hypothesis dilemma is avoided by appealing to long horizon trading strategies.

Our testing procedure adjusts for the influence of transaction costs and serial correlation in incremental trading profits. Employing both equal- and value-weighted stock portfolios using monthly data on UK stocks, we find evidence in favor of statistical arbitrage for 9 out of the 20 portfolios considered, all involving stocks that initiate/resume paying dividends. Value-weighted portfolios result in lower profits than equal-weighted portfolios indicating the presence of a “small stock” effect. Profits, however, still remain considerable and significant. It should be noted that complicating the trading profit dynamics by introducing the growth rate in the mean trading profit results in none of the strategies passing the statistical arbitrage test. Comparing several measures of fit of the CM model with those of the UM model we conclude that there is no need to complicate the trading profit process and weaken the power of the test.

The estimates of mean monthly profits for the statistical arbitrage strategies range

⁴⁰Hogan et al. (2004) reach the same conclusion regarding incremental trading profit processes derived from momentum and value strategies.

from about 1 percent to almost 5 percent per month, depending on the investment horizon. However, we caution investors against casually employing the most profitable trading strategies, as these may suffer intermediate losses and incur loss probabilities converging only slowly to zero.

All in all, our results suggest that several trading opportunities that converge to riskless arbitrages with decreasing time-averaged variances exist in the UK market, providing evidence against (semi-strong) market efficiency. Strategies involving dividend omissions could also be profitable, and perhaps test positively for statistical arbitrage, if for horizons longer than 6 months we were to reverse the trading strategy and go long of dividend omitting stocks and short the market (like with initiation strategies). It may be that dividend omitting stocks in the UK exhibit “overreaction” and not “underreaction” in the long-term as documented for the US by Michaely et al. (1995). We refrain from performing such an “ex-post” exercise that could be open to data-snooping criticisms.

Table 4.1

Summary Statistics for the Incremental Profits from Dividend Announcement Strategies					
Panel A: Equal-Weighted Portfolios					
	Min	Max	Median	Mean	Std. Dev.
INI 3	-0.1834	0.4083	0.0022	0.0095	0.0700
INI 6	-0.5042	0.6804	0.0033	0.0181	0.1139
INI 12	-0.6575	0.6629	0.0053	0.0170	0.1423
INI 18	-0.7938	1.0029	0.0196	0.0395	0.2200
INI 24	-1.2589	1.8894	0.0045	0.0312	0.2997
OMI 3	-0.6310	0.3416	0.0064	0.0044	0.1486
OMI 6	-0.7420	0.6108	0.0309	0.0094	0.2221
Panel B: Value-Weighted Portfolios					
INI 3	-0.1712	0.4890	0.0012	0.0083	0.0695
INI 6	-0.5042	0.4712	0.0110	0.0125	0.1053
INI 12	-0.6575	0.5193	0.0054	0.0123	0.1463
INI 18	-0.7938	0.9680	0.0107	0.0224	0.2288
INI 24	-1.2568	1.2564	0.0020	0.0175	0.2907
OMI 3	-0.6123	0.3210	0.0039	0.0041	0.1439
OMI 6	-0.7345	0.6412	0.0234	0.0095	0.2212

Note: Summary statistics for dividend initiation (INI) and dividend omission (OMI) portfolios. Sample period is from March 1984 to May 2002 for the INI portfolios and June 1992 to May 2002 for the OMI portfolios. The number next to INI/OMI indicates the length of the holding period. Portfolio returns are adjusted for the influence of transaction costs. The risk free asset is used to finance the portfolios.

Table 4.2

Constrained Mean Correlated (CMC) Statistical Arbitrage Tests								
Panel A: Equal-Weighted Portfolios								
Portfolio	μ	$t - stat$	σ ($p - val$)	λ	ϕ ($p - val$)	$H1$ ($\mu > 0$)	$H2$ ($\lambda < 0$)	$H1 + H2$
INI 3	0.0107	1.96	0.1497(0.00)	-0.1836	0.0519(0.229)	0.009	0.000	0.001
INI 6	0.0210	2.31	0.2116(0.00)	-0.1505	0.0730(0.148)	0.002	0.001	0.003
INI 12	0.0223	1.75	0.4351(0.00)	-0.2767	0.1002(0.072)	0.004	0.000	0.004
INI 18	0.0497	2.60	0.9100(0.00)	-0.3669	0.1969(0.005)	0.000	0.000	0.000
INI 24	0.0483	1.87	0.8938(0.00)	-0.2902	0.2678(0.000)	0.001	0.000	0.001
OMI 3	0.0148	0.55	0.4206(0.00)	-0.3177	0.2281(0.016)	0.105	0.000	0.105
OMI 6	0.0198	0.45	0.6851(0.00)	-0.3498	0.2895(0.007)	0.114	0.000	0.114
Panel B: Value -Weighted Portfolios								
INI 3	0.0095	1.72	0.1846(0.00)	-0.2402	0.1082(0.065)	0.015	0.000	0.015
INI 6	0.0150	1.72	0.2481(0.00)	-0.2096	0.0961(0.086)	0.012	0.000	0.012
INI 12	0.0114	1.23	0.7865(0.00)	-0.4216	0.0597(0.193)	0.067	0.000	0.067
INI 18	0.0292	1.41	0.9210(0.00)	-0.4270	-0.0192(0.609)	0.005	0.000	0.005
INI 24	0.0278	0.88	0.8865(0.00)	-0.1750	0.0230(0.370)	0.123	0.045	0.178
OMI 3	0.0152	0.96	0.4101(0.00)	-0.2986	0.1870(0.045)	0.110	0.000	0.110
OMI 6	0.0199	0.82	0.7012(0.00)	-0.3210	0.2561(0.009)	0.119	0.000	0.119

Note: Parameter estimates and corresponding p-values for the constrained mean test of statistical arbitrage. Sample period is from March 1984 to May 2002 for the INI portfolios and June 1992 to May 2002 for the OMI portfolios. The number next to INI/OMI indicates the length of the holding period. Portfolio returns are adjusted for the influence of transaction costs. The risk free asset is used to finance the portfolios. H1 and H2 denote the p-values from statistical arbitrage tests which test whether the portfolio's mean monthly incremental trading profit is positive and whether its time-averaged variance is declining over time. The sum of the H1 and H2 columns is the p-value for the statistical arbitrage test. The t-statistic on the mean monthly trading profit is provided for comparison.

Table 4.3

Comparison between Constrained Mean Correlated (CMC) and Unconstrained Mean Correlated (UCMC) Models						
Panel A: Equal Weighted Portfolios						
Portfolio	RMSE (CMC)	RMSE (UCMC)	SSR (CMC)	SSR (UCMC)	θ (p-value)	LRT
INI 3	1.418	1.414	1.003	1.003	0.4688 (0.301)	0.000
INI 6	2.314	2.305	1.005	1.006	0.5205 (0.218)	0.000
INI 12	2.919	2.911	1.009	1.009	0.1536 (0.373)	0.000
INI 18	4.449	4.450	1.040	1.034	0.1918 (0.324)	0.001
INI 24	4.958	5.043	1.118	1.103	0.6156(0.178)	0.020
OMI 3	2.189	2.178	1.052	1.067	1.7353(0.233)	0.012
OMI 6	3.274	3.273	1.085	1.080	0.3784(0.368)	0.000
Panel B: Value-Weighted Portfolios						
INI 3	1.408	1.406	1.012	1.011	0.4150 (0.344)	0.000
INI 6	2.142	2.138	1.010	1.003	0.9281 (0.247)	0.000
INI 12	3.084	3.089	1.003	1.003	-0.3486 (0.249)	0.000
INI 18	4.656	4.660	1.000	1.000	0.0494 (0.465)	0.002
INI 24	4.965	4.969	1.001	1.008	-0.2961(0.451)	0.003
OMI 3	2.187	2.183	1.050	1.052	0.8764(0.321)	0.000
OMI 6	3.250	3.250	1.057	1.047	0.3210(0.346)	0.000

Note: A comparison of the root mean squared errors (RMSE) and sum of normalized squared residuals (SSR) between constrained mean (CM) and unconstrained mean (UM) models of statistical arbitrage for the INI and OMI portfolios of Table 4.2 is provided. The RMSE is based on a Monte Carlo experiment with 10,000 simulated incremental trading profit series of length equal to the observed series. The p-value for the hypothesis that the incremental trading profit of the portfolios is increasing (decreasing) over time in the cases that the point estimate of θ is positive (negative) is also presented. The Likelihood Ratio Test values are displayed and would have to exceed the critical value of 2.71 at the 10 percent level in order to reject the null hypothesis that $\theta = 0$.

Chapter 5: Summary, Discussion, and Further Research

5.1 Introduction

This thesis examines predictability in both advanced and developing stock markets using primarily time series techniques, with a view to exploiting such predictability via construction of appropriate trading strategies. To this end, the usefulness of utilizing technical trading rules that take advantage of the persistence in the returns generating process to “beat the market” has been evaluated. In addition, trading strategies to explore and exploit long-term abnormal price behavior following dividend announcements have been initiated and their feasibility as investment opportunities thoroughly appraised. The profitability of the trading strategies examined and the robustness of our results suggest that predictability in international stock markets is economically significant, casting considerable doubt on the market efficiency paradigm.

Our study of mean reversion in equity index data in Chapter 2 has been largely motivated by the inconclusiveness of the theoretical literature and the mixed empirical evidence reported to date. The growing significance of emerging markets to international investors and portfolio managers, coupled with a lack of sufficient research to characterize returns and volatility dynamics, paint the background of Chapter 3. Our reported evidence in favor of persistence in Latin American and Asian stock markets have in turn led us to construct trading strategies with the aim to exploit technical trading rule signals. Finally, Chapter 4 is inspired by a novel methodology designed to test market anomalies for statistical arbitrage and thus market efficiency, and second, by the lack of attention in the existing literature to trading strategies that could be used to exploit long-term anomalous behavior pertaining to dividend announcements, more so in markets outside the US.

The remaining of this concluding chapter presents a summary and discussion of our main findings, which include an evaluation of the methodological and empirical contribution that our thesis makes to the existing literature. The chapter ends with limitations of the thesis and suggestions for future research.

5.2 Summary and Discussion of Results

In this thesis we have examined many empirical issues relating to the modeling and exploitation of predictability in stock market data from three different perspectives, elaborated upon in three self-contained chapters.

5.2.1 Chapter 2

In Chapter 2 we investigate the existence of mean reversion in the G-7 economies using a two-factor continuous time model for national stock index data. The purpose of employing a continuous time framework to examine mean reversion is that most of the conflicting results in the literature arise from the specification of the “holding time period” in stocks, a notion which becomes at least theoretically irrelevant in a continuous time setting. Mean reversion is formulated as an “intrinsic” property of the underlying model of equity prices, that is, without explicit reference to the investment horizon over which price changes are measured. Nesting with the modeling philosophies of earlier studies, our theoretical framework assumes that stock prices are generated by the joint effect of a stationary mean-reverting component which causes predictability in returns modeled as an Ornstein-Uhlenbeck process, and a nonstationary component, modeled by an Arithmetic Brownian motion process, which produces white noise in the continuously compounded returns. Thus, our model can be regarded as the continuous time-equivalent of Fama and French’s (1988) approach. As such, it can replicate previous empirical findings including the famous U-shaped pattern in returns autocorrelations over “discrete” investment

horizons, and requires only information embedded in conventional returns autocorrelation tests. Reduced form expressions of the slope coefficient that embodies the continuous time parameters are derived, without relying on crude approximations of the continuous time stochastic processes. In turn, a methodology is developed for identifying the continuous-time parameters of interest from unconditional covariances over non-overlapping intervals, slope coefficients, and unconditional means of stock returns.

The focus is on the effects of the “intrinsic” continuous time mean reverting coefficient in establishing the autocorrelation patterns observed in developed market stock returns and suggested in the existing literature. Since mean reversion is the maintained assumption of the model at all horizons, it is appropriate to infer correlations at long horizons from correlations at short horizons (discretization intervals) over which continuous-time models are more often estimated. The estimation procedure obviates the need for employing long time series as the recovery of the continuous time parameters from discrete data sets is achieved from relatively short time series sampled at high frequencies. This, in turn, allows us to use non-overlapping data to avoid spurious coefficient estimates. Using stock index data for twenty years (1982-2002), our method produces pervasive support for the existence of mean reversion in the G-7 markets excluding Japan. For the first time in the literature, we report statistically significant evidence of mean reversion in daily data for Canada, France, Germany, Italy, and the UK, while mean reversion in weekly data is detected for the US. The evidence is robust to the inclusion of dividends in stock market indices, and we have indications that market microstructure effects cannot account for our significant findings.

Furthermore, the results suggest that markets react faster to temporary shocks than other studies have suggested. While previous studies generally argue that the half-life of mean reversion ranges between three to five years, using more recent data at high frequencies we find that the speed of mean reversion towards the specified stochastic

trend path has risen, implying a lower degree of persistence in the temporary component of prices. This is possibly a result of more competition in the marketplace leading to faster price corrections.

5.2.2 Chapter 3

In Chapter 3 we have aimed to characterize the stock return dynamics of four Latin American (Argentina, Brazil, Mexico, Chile) and four Asian (Indonesia, Philippines, Taiwan, Thailand) emerging capital market economies and assess the profitability of popular trading rules in these markets. A previously unexplored data set consisting of daily MSCI stock index prices between 01/01/1988 and 31/05/2002 is employed, which is constructed so as to provide benchmarks that accurately represent the opportunities available to the international institutional investor. To be consistent with the vast majority of previous research conducted in ECM, and since we are interested in the profitability of these markets from the perspective of the international investor, dollar denominated prices are employed.

Given the widespread findings of long memory in the volatility of stock returns and suggestions that ECM returns, unlike developed stock markets, are likely to exhibit long memory in-the-mean effects, we employ the double long memory ARFIMA-FIGARCH framework as a starting point for the econometric analysis of the returns processes of the markets in question. To the best of our knowledge, this is the first time in the literature this framework has been employed to study stock returns dynamics. Using the general-to-specific methodology and a number of diagnostic tests to choose between competing nested models, we arrive at the most parsimonious representation of the returns process in each market, which does not involve long memory in the mean for any market. Instead, it is found that persistence in the conditional mean of ECM returns is better described by low-order autoregressive processes, while conditional volatility dynamics exhibit statistically

significant long memory effects, in agreement with results from developed market studies.

The trading rules, and specifications of those rules, that we employ to take advantage of the observed persistence in ECM return dynamics appear in previous academic research, and though subject to a survivorship bias, were very popular with traders earlier than the start of our sample period. We thus mitigate data snooping concerns not only by using a novel data set, but also by applying well-known rules (VMA and TRB) and reporting results from all rule specifications. Our trading rule results question the argument made by developed market studies that the predictive ability of trading rules is uncovered if long data series are considered. Strong support is provided for the forecasting ability of technical analysis in ECM, even after accounting for microstructure effects such as nonsynchronous trading biases: In total, disregarding statistical significance, 110 out of the 112 rules examined produce average buy signal returns greater than sell signal returns, indicating that technical trading strategies are almost always correct in predicting the direction of change in the price series in emerging markets. 69 percent of the rules (77 out of the 112) produce buy signals returns which are not only positive, but also statistically different from corresponding negative sell signal returns using standard statistical tests, demonstrating profit potential. Although trading rule results suggest that both Asian and Latin American market returns are predictable, a higher degree of predictability is uncovered in Asian markets, which account for 65% of the significant buy-sell returns using the VMA models and for 62% with the TRB rules. Moreover, the evidence of predictability in Latin American markets seems to be concentrated in Chile, particularly for VMA rules, while Argentina exhibits no significant buy-sell spreads at conventional levels with either VMA or TRB rules.

The trading outcomes and the choice of the modeling framework are further reinforced by bootstrap simulations of the “favorite” returns generating process in each market. As expected, when considering the significance of the trading rule results relative to the

simulated model for each market, the degree of trading rule predictability drops. For example, simulated p-values reveal that on aggregate only 10 VMA rule buy-sell spreads remain significant at the 5 percent level relative to the simulated distribution (45 buy-sell returns significant with standard t-ratios). This implies that the predictability generated by the simulated returns processes explains to a certain extent the predictability in the actual index data. This is particularly the case for the Latin American markets which account for only 2 of the 25 significant VMA models when the simulated distribution is considered, both found in Chilean results. Overall, the simulations reveal that the underlying statistical returns models better capture conditional mean dynamics in Latin American as opposed to Asian markets. Conditional volatility dynamics are very well replicated in all markets with both types of rules as indicated by the simulated p-values for buy and sell return standard deviations, providing robust evidence for the success and appropriateness of the FIGARCH volatility process.

The lower predictability uncovered in Latin American versus the Asian markets, verified both with standard and bootstrap statistical techniques, may be a natural consequence of the more extensive liberalization measures adopted by Latin American countries, arguably leading to more transparency and efficiency of their stock markets. However, since both statistical methods reveal that in Asian markets sell signal returns have higher predictive power than buy signal returns, we gauge the robustness of the results to the exclusion of the Asian crisis period for the Asian markets, during which sizeable negative return outliers have been recorded. We find that excluding the Asian crisis period from the analysis reduces buy-sell returns from following trading rule signals, but still predictability remains higher in Asian than Latin American countries. If there are no compelling microstructure arguments which can explain this difference in results between the two regions, we are inclined to believe that the different degree of integration with the world market could rationalize our findings.

We also employ the “double-or-out” trading scheme to evaluate whether trading rule signals can be executed profitably in the markets under investigation. The trading strategy outperforms the buy-and-hold benchmark across both VMA and TRB type rules in all markets prior to transaction costs, confirming findings of predictability, and yielding higher pre-trading cost returns in Asian markets. Indonesia exhibits the highest return across all markets for both VMA and TRB rules. In contrast with previous studies in developed markets, we report break-even costs for the double-or-out strategy for VMA rules that exceed estimated transaction costs. VMA rules appear consistently profitable in Asian markets, with some rules allowing profits in Latin American markets as well. Particularly for the former markets, profits can reach a few percentage points per trade for a significant number of rules even in the presence of transaction costs. This finding is relatively robust to the exclusion of the Asian crisis period from the analysis. Finally, excess returns do not seem to come at the expense of higher risk, as the riskiness of the trading strategy compares favorably with the volatility of the buy-and-hold returns.

All in all, our results cast doubt on the weak form efficiency of ECM economies. It is unlikely that predictability in ECM stock returns can be explained away by time-varying risk premia in the context of equilibrium models as buy signals, which pick periods of higher returns than sell signals, are generally associated with lower volatility of returns. Seasonalities cannot explain the negative returns following sell signals either, since sell signals account for a large fraction of trading days.

5.2.3 Chapter 4

In Chapter 4 we carry out an empirical investigation of trading strategies involving announcements of considerable changes in dividend policy in the UK, such as dividend initiations/resumptions and dividend omissions. We are primarily interested in the profitability of our strategies, but before judging their feasibility as investment tools we also

evaluate their risk attributes and the probability of making a loss over time. To this end, we employ the SA framework of Hogan et al. (2004) which takes account of the above matters and allows one to confidently reject the EMH if trading profits from market anomalies strategies conform to their definition of SA.

The long-term impact on stock market performance of dividend announcements has only been evaluated in the US market, albeit not conclusively. In particular, the profitability of trading strategies to exploit abnormal behavior following dividend announcements has not been dealt with even in a US context. Motivated by US suggestions of a positive price drift following dividend initiations and a negative price drift following dividend omissions, we construct a trading strategy whereby a long position is taken in portfolios of dividend initiating/resuming stocks matched by a short position in the FTSE All Share index; on the contrary, a short position is taken in portfolios of dividend omitting stocks and a matching long position in the index. These zero investment positions are held for 3, 6, 12, 18, and 24 months following the month of portfolio formation. We employ both equal- and value-weighted stock portfolios using monthly data on UK stocks between March 1984 and May 2002 for initiations, and June 1992 to May 2002 for omissions. Our universe of stocks consists of a combined sample of 1202 dividend initiating/resuming stocks (967 initiations and 235 resumptions) and 447 cash dividend omitting stocks. The use of monthly data mitigates compounding biases in long-term returns of equity portfolios. The monthly profits of the trading strategies are adjusted downward by a “high” estimate of transaction costs for the UK stocks (2.1% round trip trading cost) and converted into pound denominated trading profits with gains and losses accruing through time according to the risk-free interest rate. Trading profits are then tested for SA using the constrained- and unconstrained- (CM and UM) mean specifications for the trading profit process as in Hogan et al. (2004). Additionally, we model serial correlation in incremental trading profits to avoid inappropriate standard errors for the model parameters.

All in all, we investigate 20 trading strategies for SA. We find that 9 out of the 10 dividend initiation/resumption strategies involving both equal- and value-weighted portfolios test positively for SA using the CM model, producing estimates of mean monthly profits ranging from about 1 percent to almost 5 percent per month, depending on the investment horizon. In general, the longer the investment horizon, the higher the profit of the strategy, which thing is consistent with a long-term positive price drift for dividend initiating stocks in the UK. As far as risk is concerned, in all cases the time-averaged variance declines fast towards zero with the number of trading months. Our results contrast with those of Boehme and Sorescu (2002) for the US, who find that the abnormal price drift is limited to only small stocks in their sample. Although profits from value-weighted portfolios are lower than profits from equal-weighted portfolios over the same investment horizon, suggesting the presence of a small stock effect, profits do remain positive and significant. It should be noted that a capital-constrained investor concerned with intermediate losses may not choose to operate the longer holding period strategies which appear more profitable. Instead, he may sacrifice potentially higher returns for a trading strategy with probability of loss becoming small enough in a shorter time frame, eg. the probability of loss falls below 5 percent for the equal-weighted INI6 strategy after just 97 months of trading compared with 160 months for the equal-weighted INI24 strategy.

In contrast with CM model results, dividend initiation strategies do not test positively for SA when the assumed trading process is further complicated by estimating the growth rate in the mean trading profits. This is because the UM model spreads the information contained in trading profits over an additional variable without offering an improved fit, thereby weakening the power of the SA test. In particular, introducing the growth rate in the mean parameter reduces the magnitude and significance of the mean profit estimates dramatically. Comparing several measures of fit of the CM model with those of the UM

model we conclude that there is no need to complicate the trading profit process.

None of the dividend omission strategies test positively for SA with either the CM or UM models. Although omission strategies (both equal- and value-weighted) produce positive profit estimates for up to a holding period of 6 months, these are not statistically significant at conventional levels. The dividend omission strategies as formulated in this chapter - given the Michaely et al (1995) findings - produce negative mean trading profits for the longer investment horizons, and testing them for SA is immaterial. In general, our results for omissions in the UK contrast sharply with the findings of Michaely et al. (1995) for the US, who observes significant negative price drifts for up to 3 years following dividend omissions.

Overall, roughly half of the dividend announcement trading strategies we examine test positively for SA. The existence of significant profits is only confined to initiations/resumptions strategies (asymmetry uncovered). Our findings suggest the existence of several trading opportunities that converge to riskless arbitrages with decreasing time-averaged variances, a result difficult to reconcile with market efficiency. The results are robust to the small stock effect and to the incorporation of transaction costs. Our work adds to the evidence provided by Hogan et al. (2004) against efficiency of the US market using momentum and value trading strategies.

5.3 Delimitations and Further Research

The results of the thesis are highly promising whilst at the same time not conclusive. The results are promising because they indicate that significant levels of profitability can be achieved using strategies to exploit predictability, at acceptable levels of risk, even in the presence of transaction costs. At the same time we believe that the results are not conclusive because the true tests of trading methodologies cannot be evaluated in a research environment using historical data, but must ultimately be performed in a true trading

environment using real prices, real costs, and real trading infrastructure, which allows for position management and the assimilation of more information (eg. combinations of technical indicators) before the trading decision. Having made this caveat, we do believe our results demonstrate significant potential and are of interest both to the academic and to the investment community.

Our first research project has modeled mean-reverting behavior in the dynamics of equity index prices. Because our aim was to replicate previous modeling attempts and point out intrinsic deficiencies, our continuous-time model invokes the normality assumption which could be questionable for stock returns. A bootstrap procedure can be performed, possibly of the “moving blocks” type or the “stationary bootstrap” of Politis and Romano (1994) which maintain dependencies in the data, to further test the validity of this assumption.

The second research project has modeled persistence in ECM return dynamics and “traded” our findings via a number of Moving Average and Trading Range Break Rules. Given our evidence in favor of profitability, particularly in countries that have not liberalized their markets extensively over our sample period, it would be interesting for future research to evaluate whether similar results can be found for other markets at a similar stage of development. Moreover, the Asian markets offer interesting ground for future research to investigate whether a gradual transition to a developed market, “efficient-type” status has emerged after the Asian crisis (by which time the Asian economies dismantled their capital controls and accelerated liberalization measures), leading to a significant decline in the predictability and profitability of trading rules. On the methodological side, one could evaluate our trading rule results on the basis of alternative returns generating mechanisms using bootstrap procedures, at the same time drawing inferences about the validity of different statistical specifications. For example, it would be interesting in the future when sufficient data becomes available to investigate whether foreign investment

flow in ECM significantly affects the returns generating process. The latter could be done, for instance, by including the dollar amount of net daily trades by foreigners as an independent variable in the statistical model of returns.

The final research project evaluates market efficiency in the UK using trading strategies that attempt to exploit abnormal price behavior following dividend announcements. As was pointed out, SA is a very powerful way of assessing the EMH in an asset pricing free framework. On the empirical side, tests of SA could be extended to cover potentially the full universe of previously documented market “anomalies”, and in across other than the US market. Moreover, dividend announcement trading strategies in the UK can be re-evaluated with bigger data sets in the future. From a corporate finance perspective, it would also be interesting to disentangle the dividend from the earnings effect in the context of our trading strategies, particularly in the UK where firms make concurrent earnings and dividend announcements. On methodological issues, one potential area of future research would be to relax the Bonferroni inequality employed in the SA test with a more computationally intensive monte carlo procedure in order to simulate the critical values underlying the joint hypothesis test. The empirical discrepancy surrounding the CM and UM models may thus be resolved and facilitate the estimation of even more general trading profit dynamics.

References

- [1] Admati, A., Pfleiderer, P., 1989. Divide and Conquer: A Theory of Intraday and Day-of-the-Week Mean Effects . *The Review of Financial Studies* 2, 189-223.
- [2] Agiakloglou, C., Newbold, P., Wohar M., 1993. Bias In An Estimator Of The Fractional Difference Parameter. *Journal of Time Series Analysis* 14(3), 235-246.
- [3] Aharony, J., Swary, I., 1980. Quarterly Dividend and Earnings Announcements and Stockholders' Returns: An Empirical Analysis. *Journal of Finance* 35(1), 1-12.
- [4] Alexander, S., 1961. Price Movements in Speculative Markets: Trends or Random Walks? *Industrial Management Review* 2, 7-26.
- [5] Alexander, S., 1964. Price Movements in Speculative Markets: Trends or Random Walks? In: Cootner, P. (Ed.), *The Random Character of Stock Market Prices*, vol. 2, MIT Press, Cambridge, MA, 1964.
- [6] Alexander, C., Dimitriu, A., 2002. The Cointegration Alpha: Enhanced Index Tracking and Long-Short Equity Market Neutral Strategies. Working Paper. University of Reading.
- [7] Allen, F., Michaely, R., 1995. Dividend Policy. *Handbooks in Operations Research and Management Science* 9, Chapter 25, in R. Jarrow et al. Eds., Amsterdam, Elsevier-Science.
- [8] Ammann, M., Herriger, S., 2002. Relative Implied-Volatility Arbitrage with Index Options. *Financial Analysts Journal*, 42-55.
- [9] Andersen, T.G., Bollerslev, T., 1997. Heterogeneous Information Arrivals And Return Volatility Dynamics: Uncovering The Long-Run Frequency Returns. *Journal of Finance* 52, 975-1005.

- [10] Andersen, T.G., Bollerslev, T., 1998. Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, And Longer Run Dependencies. *Journal of Finance* 53, 219-265.
- [11] Andersson, M.K., Gredenhoff, M.P., 1998. Robust Testing For Fractional Integration Using The Bootstrap. *Working Paper Series in Economics and Finance* 218, Stockholm School of Economics.
- [12] Arnold, L., 1974. Stochastic Differential Equations: Theory and Applications. Wiley, New York.
- [13] Asquith, P., Mullins, D.W., 1983. The Impact Of Initiating Dividend Payments On Shareholders' Wealth. *Journal of Business* 56(1), 77-96.
- [14] Baillie, R.,T., 1996. Long Memory Processes And Fractional Integration In Econometrics. *Journal of Econometrics* 73, 5-59.
- [15] Baillie, R.,T., 1998. Real And Spurious Long-Memory Properties Of Stock-Market Data: Comment. *Journal of Business and Economic Statistics* 16, 273-275.
- [16] Baillie, R.T., Bollerslev, T., Mikkelsen, H.O., 1996. Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* 74, 3-30.
- [17] Baillie, R.T., Cecen, A.A., Han, Y.W., 2000. High Frequency Deutsche Mark-US Dollar Returns: FIGARCH Representations And Non Linearities. *Multinational Finance Journal* 4, 247-267.
- [18] Baillie, R.T., Han Y.W., Koul, H.L., 2002. A High Frequency Perspective on the Forward Premium Anomaly. Working Paper.

- [19] Baillie, R.T., Han Y.W., Kwon, T., 2002. Further Long Memory Properties of Inflationary Shocks. *Southern Economic Journal* 68, 496-510.
- [20] Balachandran, B., Cadle, J., Theobald, M., 1996. Interim Dividend Cuts and Omissions in the UK. *European Financial Management* 2, 23-38.
- [21] Ball, R., Kothari, S.P., 1989. Nonstationary Expected Returns: Implications for Tests of Market Efficiency and Serial Correlations in Returns. *Journal of Financial Economics* 25(1), 51-74.
- [22] Balvers, R., Wu, Y., Gilliland, E., 2000. Mean Reversion across National Stock Markets and Parametric Contrarian Investment Strategies. *Journal Of Finance* 55, 745-772.
- [23] Barber, B.M., Lyon, J.D., 1997. Detecting Long-Run Abnormal Stock Returns: The Empirical Power and Specification of Test Statistics. *Journal of Financial Economics* 43(3), 341-372.
- [24] Barberis, N., Shleifer, A., Vishny, R., 1998. A Model Of Investor Sentiment. *Journal of Financial Economics* 49(3), 307-343.
- [25] Barkoulas, J.T., Baum, C.F., Travlos, N., 2000. Long Memory in the Greek Stock Market. *Applied Financial Economics* 10 (2), 177-84.
- [26] Bekaert, G., 1995. Market Integration And Investment Barriers In Emerging Equity Markets, *World Bank Economic Review* 9, 75-107.
- [27] Bekaert, G., Erb, C.B., Harvey, C.R., Viskanta, T.E., 1998. Distributional Characteristics Of Emerging Market Returns And Asset Allocation. *Journal of Portfolio Management* 24, 102-116.

- [28] Bekaert, G., Harvey, C.R., 1995. Time-Varying World Market Integration. *Journal of Finance* 50(2), 403-444.
- [29] Bekaert, G., Harvey, C.R., 1997. Emerging Equity Market Volatility. *Journal of Financial Economics* 43, 29-77.
- [30] Bekaert, G., Harvey, C.R., 2000. Foreign Speculators And Emerging Equity Markets. *Journal of Finance* 55, 565-613.
- [31] Bekaert, G., Harvey, C.R., Lumsdaine, R.L., 2002. Dating The Integration Of World Equity Markets. *Journal of Financial Economics* 65, 203-247.
- [32] Bekaert, G., Harvey, C.R., 2003. Emerging Market Finance. *Journal of Empirical Finance* 10, 3-55
- [33] Bekaert, G., Urias, M., 1996. Diversification, Integration And Emerging Market Closed-End Funds. *Journal of Finance* 51, 835-869.
- [34] Bekaert, G., Urias, M., 1999. Is there a free lunch in emerging market equities? *Journal of Portfolio Management* 25, 83-95.
- [35] Benartzi, S., Michaely, R., Thaler, R., 1997. Do Changes in Dividends Signal the Future or the Past? *Journal of Finance* 52(3), 1007-1034.
- [36] Beran, J., 1994. Statistics for Long Memory Processes. London, UK: Chapman and Hall.
- [37] Bernard, V.L., Thomas, J.K., 1989. Post-Earnings-Announcement Drift: Delayed Price Response Or Risk Premium? *Journal of Accounting Research* 27(Supp), 1-48.
- [38] Bernard, V.L., Thomas, J.K., 1990. Evidence that Stock Prices do not Fully Reflect the Implications of Current Earnings for Future Earnings. *Journal of Accounting and Economics* 13(4), 305-340.

- [39] Bernardo, A.E., Ledoit, O., 2000. Gain, Loss, and Asset Pricing. *Journal of the Political Economy* 108, 144-172.
- [40] Bessembinder, H., Chan, K., 1995. The Profitability of Technical Trading Rules in the Asian Stock Markets. *Pacific-Basin Finance Journal* 3 (2/3), 257-284.
- [41] Bessembinder, H., Chan, K., 1998. Market Efficiency and the Returns to Technical Analysis. *Financial Management* 27 (2), 5-17.
- [42] Bessembinder, H., Hertzel, M., 1993. Return Autocorrelations Around Non Trading Days. *The Review of Financial Studies* 6, 155-189.
- [43] Beveridge, S., Nelson, C.R., 1981. A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components With Particular Attention to Measurement of the Business Cycle. *Journal of Monetary Economics* 7, 151-174.
- [44] Bhattacharya, S., 1979. Imperfect Information, Dividend Policy, and 'The Bird In The Hand' Fallacy. *Bell Journal of Economics* 10(1), 259-270.
- [45] Black, F., Jensen, M.C., Scholes, M., 1972. The Capital Asset Pricing Model: Some Empirical Tests. In Jensen, M. (Ed.) *Studies in the Theory of Capital Markets*, Praeger, New York.
- [46] Boehme, R.D., Sorescu, S.M., 2002. The Long-Run Performance Following Dividend Initiations and Resumptions: Underreaction or Product of Chance? *Journal of Finance* 57(2), 871-900.
- [47] Bohan, J., 1981. Relative Strength: Further Positive Evidence. *Journal of Portfolio Management* 7, 39-46.
- [48] Bollerslev, T., 1986. Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* 31, 307-327.

- [49] Bollerslev, T., 1988. On the Correlation Structure for the GARCH Process. *Journal of Time Series Analysis* 9, 121-131.
- [50] Bollerslev, T., Mikkelsen, H.O., 1996. Modeling And Pricing Long Memory In Stock Market Volatility. *Journal of Econometrics* 73, 151-184.
- [51] Bollerslev, T., Wooldridge, J.,M., 1992. Quasi-Maximum Likelihood Estimation of Dynamic Models with Time Varying Covariances. *Econometric Reviews* 11, 143-172.
- [52] Bondarenko, O., 2003. Statistical Arbitrage and Securities Prices. *Review of Financial Studies* 16, 875-919.
- [53] Bougerol, P., Picard, N.,M., 1992. Stationarity of GARCH Processes and of Some Nonnegative Time Series. *Journal of Econometrics* 52, 115-127.
- [54] Brav, A., Geczy C., Gompers, P.A., 2000. Is the Abnormal Return Following Equity Issuances Anomalous? *Journal of Financial Economics* 56(2), 209-250.
- [55] Breidt, F.J., Crato, N., De Lima, P., 1998. The Detection And Estimation Of Long Memory In Stochastic Volatility. *Journal of Econometrics* 83, 325-348.
- [56] Brickley, J.A., 1983. Shareholder Wealth Information Signaling and the Specially Designated Dividend: An Empirical Study. *Journal of Financial Economics* 12(2), 187-210.
- [57] Brock, W.A., Dechert, W.D., Scheinkman, J.A., LeBaron, B., 1996. A Test For Independence Based On The Correlation Dimension. *Econometric Reviews* 15, 197-235.
- [58] Brock, W.A., Lakonishok, J., and LeBaron, B., 1992. Simple Technical Trading Rules And The Stochastic Properties Of Stock Returns. *Journal of Finance* XLVII, 1731-1764.

- [59] Brush, J.S., Boles, K.E., 1983. The Predictive Power of Relative Strength and the CAPM. *Journal of Portfolio Management* 9, 20-23.
- [60] Burgess, A.N., 1999. A Computational Methodology for Modeling the Dynamics of Statistical Arbitrage. Unpublished PhD Thesis, London Business School.
- [61] Campbell, J.Y., Lo, A.W., MacKinlay, A.C., 1997. The Econometrics of Financial Markets. Princeton University Press, Princeton, N.J.
- [62] Canina, L., Michaely R., Thaler, R., Womack, K., 1998. Caveat Compounder: A Warning About Using the Daily CRSP Equal-Weighted Index to Compound Long-Run Excess Returns. *Journal of Finance* 53(1), 403-416.
- [63] Chan, L.K.C., Jegadeesh, N., Lakonishok, J., 1996. Momentum strategies. *Journal of Finance* 51, 1681-1713.
- [64] Charest, G., 1978. Dividend Information, Stock Returns and Market Efficiency - II. *Journal of Financial Economics* 6(2/3), 297-330.
- [65] Chelley-Steely, P.L., Steely, J.M., 1997. The Impact of Portfolio Diversification on Trading Rule Profits: Some Evidence for UK Share Portfolios. *Journal of Business Finance and Accounting* 24, 759-779.
- [66] Cheung, Y.W., 1993. Long Memory In Foreign-Exchange Rates. *Journal of Business and Economic Statistics* 11(1), 93-101.
- [67] Cheung, Y.W., Lai, K.S., 1995. A Search For Long Memory In International Stock Market Returns. *Journal of International Money and Finance* 14(4), 597-615.
- [68] Chopra, N., Lakonishok, J., Ritter, J.R., 1992. Measuring Abnormal Performance: Do Stocks Overreact? *Journal of Financial Economics* 31(2), 235-268.

- [69] Choudry, T., 1996. Stock Market Volatility and the Crash of 1987: Evidence from Six Emerging Markets. *Journal of International Money and Finance* 15, 969-981.
- [70] Christie, W.G., 1990. Dividend Yield and Expected Returns: The Zero-Dividend Puzzle. *Journal of Financial Economics* 28(1/2), 95-126.
- [71] Cochrane, J.H., 1988. How Big Is The Random Walk In GNP? *Journal of Political Economy* 96(5), 893-920.
- [72] Cochrane, J.H., Saa-Requejo, J., 2000. Beyond Arbitrage: Good Deal Asset Price Bounds in Incomplete Markets. *Journal of the Political Economy* 108, 79-119.
- [73] Conrad, J., Kaul, G., 1989. Mean Reversion in Short-Horizon Expected Returns. *The Review of Financial Studies* 2, 225-240.
- [74] Conrad, J., Kaul, G., 1993. Long-Term Market Overreaction or Biases in Computed Returns? *Journal of Finance* 48(1), 39-64.
- [75] Conrad, J., Kaul, G., 1998. An Anatomy Of Trading Strategies. *Review of Financial Studies* 11(3), 489-519.
- [76] Conrad, J., Kaul, G., Nimalendran, M., 1991. Components of Short-Horizon Individual Security Returns. *Journal of Financial Economics* 29, 365-384.
- [77] Corrado, C.J., Lee, S.H., 1992. Filter Rule Tests of the Economic Significance of Serial Dependence in Daily Stock Returns. *Journal of Financial Research* 15, 369-387.
- [78] Crato, N., 1994. Some International Evidence Regarding The Stochastic Memory Of Stock Returns. *Applied Financial Economics* 4(1), 33-39.
- [79] Crato, N., De Lima, P.J.F., 1994. Long-Range Dependence In The Conditional Variance Of Stock Returns. *Economics Letters* 45(3), 281-285.

- [80] Dacorogna, M.M., Muller, U.A., Nagler, R.J., Olsen, R.B., Pictet, O.V., 1993. A Geographical Model For The Daily And Weekly Seasonal Volatility In The Foreign Exchange Market. *Journal of International Money and Finance* 12(4), 413-438.
- [81] Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor Psychology And Security Market Under- and Overreactions. *Journal of Finance* 53(6), 1839-1885.
- [82] Davidson, R., MacKinnon, J.G., 1999. The Size Distortion Of Bootstrap Tests. *Econometric Theory* 15(3), 361-377.
- [83] DeAngelo, H., DeAngelo, L., Skinner, D.J., 1990. Dividend Policy and Financial Distress: An Empirical Investigation of Troubled NYSE Firms. *Journal of Finance* 45, 1415-1431.
- [84] DeAngelo, H., DeAngelo, L., Skinner, D.J., 1992. Dividends and Losses. *Journal of Finance* 47, 1837-1863.
- [85] DeAngelo, H., DeAngelo, L., Skinner, D.J., 1996. Reversal of Fortune: Dividend Signalling and the Disappearance of Sustained Earnings Growth. *Journal of Financial Economics* 40, 341-371.
- [86] De Bondt, W.F.M., Thaler, R., 1985. Does the Stock Market Overreact? *Journal of Finance* 40, 793-807.
- [87] De Bondt, W.F.M., Thaler, R., 1987. Further Evidence on Investor Overreaction and Stock Market Seasonality. *Journal of Finance* 42, 557-581.
- [88] De Santis, G., 1993. Asset Pricing and Portfolio Diversification: Evidence from Emerging Financial Markets. *World Bank Symposium on Portfolio Investment in Developing Countries*, Washington, D.C.

- [89] De Santis, G., Imrohoroğlu, S., 1997. Stock Returns And Volatility In Emerging Financial Markets. *Journal of International Money and Finance* 16, 561-579.
- [90] De Roon, F.A., Nijman, T.E., Werker, B.J., 2001. Testing For Mean-Variance Spanning With Short Sales Constraints And Transaction Costs: The Case Of Emerging Markets. *Journal of Finance* 56, 721-742.
- [91] Dharan, B.G., Ikenberry, D.L., 1995. The Long-Run Negative Drift of Post-Listing Stock Returns. *Journal of Finance* 50(5), 1547-1574.
- [92] Dickey, D.A., Fuller, W.A., 1981. Likelihood Ratio Statistics for Autoregressive Time Series With a Unit Root. *Econometrica* 49(4), 1057-1072.
- [93] Diebold, F.X., Inoue, A., 2001. Long Memory And Regime Switching. *Journal of Econometrics* 105, 131-159.
- [94] Ding, Z., Granger, C.W.J., Engle, R.F., 1993. A Long Memory Property Of Stock Market Returns And A New Model. *Journal of Empirical Finance* 1(1), 83-106.
- [95] Ding, Z., Granger, C.W.J., 1996. Modeling Volatility Persistence Of Speculative Returns: A New Approach. *Journal of Econometrics* 73, 185-215.
- [96] Eberhart, A.C., Maxwell, W.F., Siddique, A.R., 2004. An Examination of Long-Term Abnormal Stock Returns and Operating Performance Following R&D Increases. *Journal of Finance* 59(2), 623-651.
- [97] Eberhart, A.C., Siddique, A.R., 2002. The Long-Term Performance of Corporate Bonds (and Stocks) Following Seasoned Equity Offerings. *Review of Financial Studies* 15(5), 1385-1406.
- [98] Eckbo, E.B., Masulis, R.W., Norli, O., 2000. Seasoned Public Offerings: Resolution of The 'New Issues Puzzle'. *Journal of Financial Economics* 56(2), 251-291.

- [99] Edison, H., Warnock, F., 2003. A simple measure of the intensity of capital controls. *Journal of Empirical Finance* 10, 83-105.
- [100] Edwards, S., Gómez Biscarri, J., Pérez de Gracia, F., 2003. Stock Market Cycles, Financial Liberalization and Volatility. *Journal of International Money and Finance* 22, 925-955.
- [101] Efron, B., Tibshirani, R., 1986. *Statistical Science* 1(1), 54-77.
- [102] Efron, B., Tibshirani, R., 1993. An Introduction To The Bootstrap. Chapman and Hall.
- [103] Elton, E.J., Gruber, N.J., 1995. Modern Portfolio Theory and Investment Analysis (5th edition). John Wiley, New York.
- [104] Engle, R. F., Bollerslev, T., 1986. Modelling The Persistence Of Conditional Variances. *Econometric Reviews* 5(1), 1-50.
- [105] Fama, E.F., 1965. The Behavior of Stock Market Prices. *Journal of Business* 38, 34-105.
- [106] Fama, E.F., 1970. Efficient Capital Markets. A Review of Theory and Empirical Work. *Journal of Finance* 25, 383-417.
- [107] Fama, E.F., 1991. Efficient Capital Markets: II. *Journal of Finance* 46(5), 1575-1617.
- [108] Fama, E.F., 1998. Market Efficiency, Long-Term Returns, and Behavioral Finance. *Journal of Financial Economics* 49(3), 283-306.
- [109] Fama, E.F., Blume, M., 1966. Filter Rules and Stock Market Trading. *Journal of Business* 39, 226-241.

- [110] Fama, E.F., French, K.R., 1988. Permanent And Temporary Components Of Stock Prices. *Journal of Political Economy* 96(2), 246-273.
- [111] Fama, E.F., French, K.R., 1992. The Cross-Section Of Expected Stock Returns. *Journal of Finance* 47(2), 427-466.
- [112] Fama, E.F., French, K.R., 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33(1), 3-56.
- [113] Fama, E.F., MacBeth, J., 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81, 607-636.
- [114] Fama, E.F., Schwert, G.W., 1977. Asset Returns And Inflation. *Journal of Financial Economics* 5(2), 115-146.
- [115] Fang, Y., Xu, D., 2003. The Predictability of Asset Returns: An Approach Combining Technical Analysis and Time Series Forecasts. *International Journal of Forecasting* 19, 369-385.
- [116] Freedman, D., 1981. Some Pitfalls In Large Econometric Models: A Case Study. *Journal of Business* 54(3), 479-500.
- [117] Freedman, D., 1984. On Bootstrapping Two-stage Least Squares Estimates In Stationary Linear Models. *Annals of Statistics* 12, 827-842.
- [118] Freedman, D.A., Peters, S.C., 1984a. Bootstrapping An Economic Model: Some Empirical Results. *Journal of Business and Economic Statistics* 2(2), 150-158.
- [119] Freedman, D.A., Peters, S.C., 1984b. Bootstrapping A Regression Equation: Some Empirical Results. *Journal of the American Statistical Society* 79, 97-106.
- [120] French, K., Roll, R., 1986. Stock Return Variances: The Arrival of Information and the Reaction of Traders. *Journal of Financial Economics* 17, 5-26.

- [121] French, K., Schwert, G.W., Stambaugh, R.F., 1987. Expected Stock Returns and Volatility. *Journal of Financial Economics* 19, 3-30.
- [122] Gatev, E.G., Goetzmann, W.N., Rouwenhurst, K.G., 1999. Pairs Trading: Performance of a Relative Value Arbitrage Rule. Working Paper, Yale School of Management's Financial Research Network.
- [123] Gemmill, G., 1998. Touched by Success. *Financial News Briefing Notes* 5.
- [124] Gençay, R., 1988. The Predictability of Security Returns with Simple Technical Trading Rules. *Journal of Empirical Finance* 5(4), 347-359.
- [125] Geweke J., Porter-Hudak, S., 1983. The Estimation And Application of Long Memory Time Series Models. *Journal of Time Series Analysis* 4, 221-238.
- [126] Gómez Biscarri, J., Pérez de Gracia, F., 2002. Stock Market Cycles and Stock Market Development in Spain. *Universidad de Navarra Department of Economics Working Paper* 01/02.
- [127] Gonedes, N.J., 1978. Corporate Signaling, External Accounting, and Capital Market Equilibrium: Evidence on Dividends, Income, and Extraordinary Items. *Journal of Accounting Research* 16(1), 26-79.
- [128] Granger, C.W.J., 1980. Long Memory Relationships And The Aggregation Of Dynamic Models. *Journal of Econometrics* 14(2), 227-238
- [129] Granger, C.W.J., 1998. Real And Spurious Long-Memory Properties Of Stock-Market Data: Comment. *Journal of Business and Economic Statistics* 16, 268.
- [130] Granger, C.W.J., Ding, Z., 1995. Some Properties of Absolute Returns, An Alternative Measurement of Risk. *Annales deconomie et de statistique* 40, 67-92

- [131] Granger, C.W.J., Hyung, N. 1999. Occasional structural breaks and long memory. Discussion Paper 99-14 (UCSD).
- [132] Granger, C.W.J., Joyeux, R., 1980. An Introduction to Long-memory Time Series and Fractional Differencing. *Journal of Time Series Analysis* 1, 15-30.
- [133] Granger, C.W.J., Terasvirta, T., 1999. A Simple Nonlinear Time Series Model With Misleading Linear Properties. *Economics Letters* 62, 161-165.
- [134] Grossman, S.J., Zhou, Z., 1996. Equilibrium Analysis Of Portfolio Insurance. *Journal of Finance* 51, 1379-1403.
- [135] Grullon, G., Michaely, R., Swaminathan, B., 2002. Are Dividend Changes a Sign of Firm Maturity? *Journal of Business* 75(3), 387-424.
- [136] Gunasekarage, A., Power, D.M., 2001. The Profitability Of Moving Average Trading Rules In South Asian Stock Markets. *Emerging Markets Review* 2001(2), 17-33.
- [137] Hansen, L.P., 1982. Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica* 50, 1029-1054.
- [138] Hansen, L.P., Hodrick, R.J., 1980. Forward Exchange Rates As Optimal Predictors Of Future Spot Rates: An Econometric Analysis. *Journal of Political Economy* 88(5), 829-853.
- [139] Harrison, J.M., Kreps, D.M., 1979. Martingales And Arbitrage in Multiperiod Securities Markets. *Journal of Economic Theory* 20(3), 381-408.
- [140] Harvey, C.R., 1995a. Predictable Risk And Returns In Emerging Markets. *Review of Financial Studies* 8(3), 773-816.
- [141] Harvey, C.R., 1995b. The Risk Exposure of Emerging Equity Markets. *World Bank Economic Review* 9, 19-50.

- [142] Hasbrouck, J., 1991. The Summary of Informativeness of Stock Trades: An Econometric Analysis. *The Review of Financial Studies* 4, 571-595.
- [143] Hatgioannides, J., 1995. Essays on Asset Pricing in Continuous Time. Unpublished PhD Thesis, University of London.
- [144] Healy, P.M., Palepu, K.G., 1988. Earnings Information Conveyed by Dividend Initiations And Omissions. *Journal of Financial Economics* 21(2), 149-176.
- [145] Hiemstra, C., Jones, J.D., 1997. Another Look At Long Memory In Common Stock Returns. *Journal of Empirical Finance* 4, 373-401.
- [146] Hogan, S.C., Jarrow, A.R., Teo, M., Warachka, M., 2004. Testing Market Efficiency Using Statistical Arbitrage with Applications to Momentum and Value Trading Strategies. *Journal of Financial Economics*, forthcoming.
- [147] Hong, H., Stein, J.C., 1999. A Unified Theory Of Underreaction, Momentum Trading, And Overreaction In Asset Markets. *Journal of Finance* 54(6), 2143-2184.
- [148] Hong, H., Lim, T., Stein, J.C., 2000. Bad News Travel Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. *Journal of Finance* 55, 265-295.
- [149] Hosking, J.,R.,M., 1981. Fractional Differencing. *Biometrika* 68, 165-176.
- [150] Hudson, R., Dempsey, M., Keasey, K., 1996. A Note on the Weak Form Efficiency of Capital Markets: The Application of Simple Technical Trading Rules to UK Stock Prices - 1935 to 1994. *Journal of Banking and Finance* 20, 1121-1132.
- [151] Hull, J.C., White, A., 1993. One-Factor Interest Rate Models and the Valuation of Interest-Rate Derivative Securities. *Journal of Financial & Quantitative Analysis* 28(2), p235-254.

- [152] Hurst, H.E., 1951. Long-Term Storage Capacity of Reservoirs. *Transactions of the American Society of Civil Engineers* 116, 770-808.
- [153] Ikenberry, D., Lakonishok J., Vermaelen, T., 1995. Market Underreaction to Open Market Share Repurchases. *Journal of Financial Economics* 39(2/3), 181-208.
- [154] Ikenberry, D., Lakonishok J., Vermaelen, T., 2000. Stock Repurchases in Canada: Performance and Strategic Trading. *Journal of Finance* 55(5), 2373-2397.
- [155] Ito, A., 2003. Technical Trading Rules and Nonlinear Time Series Models. *Asia-Pacific Journal of Financial Studies*.
- [156] Jacobsen, B., 1996. Long Term Dependence In Stock Returns. *Journal of Empirical Finance* 3(4), 393-417.
- [157] Jacobs, B.I., Levy, K.N., 1988. Disentagling Equity Return Regularities: New Insights and Investment Opportunities. *Financial Analysts Journal* 44, 18-43.
- [158] James Jr., F.E., 1968. Monthly Moving Averages - an Effective Investment Tool? *Journal of Financial and Quantitative Analysis* 3, 315-326.
- [159] Jarrow, R., 1988. Finance Theory. Prentice-Hall.
- [160] Jegadeesh, N., 1990. Evidence of Predictable Behavior of Security Returns. *Journal of Finance* 45, 881-898.
- [161] Jegadeesh, N., 1991. Seasonality in Stock Price Mean Reversion: Evidence From the U.S. and the U.K. *Journal of Finance* 46, 1427-1444.
- [162] Jegadeesh, N., Titman, S., 1993. Returns To Buying Winners And Selling Losers: Implications For Stock Market Efficiency. *Journal of Finance* 48(1), 65-92.
- [163] Jegadeesh, N., Titman, S., 1995. Overreaction, Delayed Reaction, and Contrarian Profits. *Review of Financial Studies* 8(4), 973-993.

- [164] Jensen, M., Benington, G., 1970. Random Walks and Technical Theories: Some Additional Evidence. *Journal of Finance* 25, 469-482.
- [165] Jensen, M.C., 1986. Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *American Economic Review* 76(2), 659-665.
- [166] John, K., Williams, J., 1985. Dividends, Dilution, and Taxes: A Signalling Equilibrium. *Journal of Finance* 40(4), 1053-1070.
- [167] Kalay, A., Loewenstein, U., 1985. Predictable Events and Excess Returns: The Case of Dividend Announcements. *Journal of Financial Economics* 14(3), 423-449.
- [168] Kamesaka, A., Wang, J., 2001. Foreign and Domestic Investors in Indonesia: Impact of the Asian Crisis to Their Trades. *Ryukoku University Working Paper*.
- [169] Kamesaka, A., Wang, J., 2003. Asian Crisis and Investor Behavior in Thailand's Equity Market. *Ryukoku University Working Paper*.
- [170] Karolyi, A.G., Kho, B.G., 2004. Momentum Strategies: Some Bootstrap Tests. *Journal of Empirical Finance*, (forthcoming)
- [171] Kasa, K., 1992. Common Stochastic Trends in International Stock Markets. *Journal of Monetary Economics* 29, 95-124.
- [172] Kaul, G., Nimalendran, M., 1990. Price Reversals: Bid-Ask Errors or Market Overreaction? *Journal of Financial Economics* 28(1/2), 67-94.
- [173] Keim, D., Stambaugh, R., 1986. Predicting Returns in the Stock and Bond Markets. *Journal of Financial Economics* 17, 357-390.
- [174] Keynes, J., M., 1936. The General Theory of Employment, Interest, and Money. Harcourt, Brace, New York.

- [175] Kim, M.J., Nelson, C.R., Startz, R., 1991. Mean reversion in Stock Prices? A Reappraisal of the Empirical Evidence. *Review of Economic Studies* 58, 515-528.
- [176] Lakonishok, J., Shleifer A., Vishny, R.W., 1994. Contrarian Investment, Extrapolation, and Risk. *Journal of Finance* 49(5), 1541-1578.
- [177] Lang, L.H.P.,Litzenberger, R.H., 1989. Dividend Announcements: Cash Flow Signalling vs. Free Cash Flow Hypothesis. *Journal of Financial Economics* 24, 181-191.
- [178] Lamoureux, C.G., Lastrapes, W.D., 1990. Persistence In Variance, Structural Change, And The GARCH Model. *Journal of Business and Economic Statistics* 8(2), 225-234.
- [179] Lehmann, B., 1990. Fads, Martingales, and Market Efficiency. *Quarterly Journal of Economics* 105, 1-28.
- [180] LeRoy, S.,F., 1989. Efficient Capital Markets and Martingales. *Journal of Economic Literature* 27, 1583-1621.
- [181] Levich, R.M., Thomas, L., 1993. The Significance of Technical Trading Rule Profits in the Foreign Exchange Market: A Bootstrap Approach. *Journal of International Money and Finance*, 451-74.
- [182] Levy, R.A., 1967a. Random Walks: Reality or Myth. *Financial Analysts Journal* 23, 69-77.
- [183] Levy, R.A., 1967b. Relative Strength as a Criterion for Investment Selection. *Journal of Finance* 22, 595-610.
- [184] Li, K., Sarker, A., Wang, Z., 2003. Diversification Benefits Of Emerging Markets Subject to Portfolio Constraints. *Journal of Empirical Finance* 10, 59-82.

- [185] Lo, A.W., 1991. Long-Term Memory In Stock Market Prices. *Econometrica* 59(5), 1279-1314.
- [186] Lo, A.W., MacKinlay, A.C., 1988. Stock Market Prices Do Not Follow Random Walks: Evidence From A Simple Specification Test. *Review of Financial Studies* 1(1), 41-66.
- [187] Lo, A.W., MacKinlay, A. G., 1990a. When are Contrarian Profits Due to Stock Market Overreaction? *The Review of Financial Studies* 3, 175-205.
- [188] Lo, A.W., MacKinlay, A.C., 1990b. An Econometric Analysis of Nonsynchronous Trading. *Journal of Econometrics* 45, 181-112.
- [189] Lo, A.W., Wang, J., 1995. Implementing Option Pricing Models when Asset Returns are Predictable. *Journal of Finance* 50, 87-129.
- [190] Lobato, I.N., Savin, N.E., 1998. Real And Spurious Long-Memory Properties Of Stock Market Data. *Journal of Business and Economic Statistics* 16, 261-267.
- [191] Lonie, A.A., Abeyratna, G., Power, D.M., Sinclair, C.D., 1996. The Stock Market Reaction To Dividend Announcements: A UK Study Of Complex Market Signals. *Journal of Economic Studies* 23(1), 32-52.
- [192] Loughran, T., Ritter, J.R., 1995. The New Issues Puzzle. *Journal of Finance* 50(1), 23-51.
- [193] Loughran, T., Ritter, J.R., 2000. Uniformly Least Powerful Tetst of Market Efficiency. *Journal of Financial Economics* 55(3), 361-389.
- [194] Lyon, J.D., Barber, B.M, Tsai, C.H., 1999. Improved Methods for Tests of Long-Run Abnormal Stock Returns. *Journal of Finance* 54(1), 165-201.

- [195] Mandelbrot, B.B., 1971. When Can Price Be Arbitraged Efficiently? A Limit To The Validity Of The Random Walk And Martingale Models. *Review of Economics and Statistics* 53(3), 225-236.
- [196] Michaely, R., Thaler, R.H., Womack, K.L., 1995. Price Reactions to Dividend Initiations And amissions: Overreaction or Drift? *Journal of Finance* 50(2), 573-608.
- [197] Miller, M.H., Rock, K., 1985. Dividend Policy Under Asymmetric Information. *Journal of Finance* 40(4), 1031-1051.
- [198] Mitchell, M.L., Stafford, E., 2000. Managerial Decisions and Long-Term Stock Price Performance. *Journal of Business* 73(3), 289-329.
- [199] Nelson, D.B., 1990. Stationary And Persistence In The GARCH (1,1) Model. *Econometric Theory* 6(3), 318-334.
- [200] Nelson, D.B., 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica* 59(2), 347-370.
- [201] Nelson, C. R., Plosser, C. I., 1982. Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications. *Journal of Monetary Economics* 10, 139-162.
- [202] Osler, C.L., Chang, P.H.K., 1995. Head and Shoulders: Not Just a Flaky Pattern. *Federal Reserve Bank of New York Staff Reports* 4.
- [203] Pagan, A., R., Sossounov, K., A., 2003. A Simple Framework for Analysing Bull and Bear Markets. *Journal of Applied Econometrics* 18(1), 23-46.
- [204] Parisi, F., Vasquez, A., 2000. Simple Technical Trading Rules Of Stock Returns: Evidence From 1987 to 1988 In Chile. *Emerging Markets Review* 2000(2), 152-164.

- [205] Perron, P., 1991. A Continuous Time Approximation to the Unstable First-Order Autoregressive Process: The Case Without An Intercept. *Econometrica* 1, 211-236.
- [206] Pesaran, M.H., Timmermann, A., 2000. A Recursive Modelling Approach to Predicting UK Stock Returns. *Economic Journal* 110(460), 159-191.
- [207] Pettit, R.R., 1972. Dividend Announcements, Security Performance, and Capital Market Efficiency. *Journal of Finance* 27(5), 993-1007.
- [208] Poitras, G., 1987. 'Golden Turtle Tracks': In Search of Unexploited Profits in Gold Spreads. *Journal of Futures Markets* 7(4), 397-412.
- [209] Poitras, G., 1997. Turtles, Fails, And Stereos: Arbitrage and the Design of Futures Spread Trading Strategies. *Journal of Derivatives* 5(2), 71-87.
- [210] Politis, R., Romano, J., 1994. The Stationary Bootstrap. *Journal of American Statistical Association* 89, 1303-1313.
- [211] Poterba, J.M., Summers, L.H., 1988. Mean Reversion In Stock Prices: Evidence And Implications. *Journal of Financial Economics* 22(1), 27-60.
- [212] Ratner, M., Leal, R.P.C., 1999. Tests of Technical Trading Strategies in the Emerging Equity Markets of Latin America and Asia. *Journal of Banking and Finance* 23, 1887-1905.
- [213] Ready, M.J., 1997. Profits from Technical Trading Rules. Working Paper, University of Wisconsin-Madison, Madison, WI.
- [214] Ready, M.J., 2002. Profits from Technical Trading Rules. *Financial Management* 31, 3-61.
- [215] Reilly, F.K., Brown, K.C., 1994. *Investment Analysis and Portfolio Management*. Dryden Press, Orlando, FL.

- [216] Richards, A.J., 1995. Comovements in National Stock Market Returns: Evidence of Predictability, but not Cointegration. *Journal of Monetary Economics* 36, 631-654.
- [217] Richards, A.J., 1997. Winner-Loser Reversals in National Stock Market Indices: Can they be Explained? *Journal of Finance* 52, 2129-2144.
- [218] Richardson, M., 1993. Temporary and Permanent Components of Stock Prices: A Skeptic's View. *Journal of Business and Economic Statistics* 11, 199-207.
- [219] Richardson, M., Smith, T., 1991. Tests of Financial Models with the Presence of Overlapping Observations. *Review of Financial Studies* 4(2), 227-254.
- [220] Richardson, M., Stock, J., 1989. Drawing Inferences from Statistics Based on Multi-Year Asset Returns. *Journal of Financial Economics* 25, 323-348.
- [221] Ritter, J.R., 1991. The Long Run Performance of Initial Public Offerings. *Journal of Finance* 46(1), 3-28.
- [222] Robinson, P.M., 1978. Statistical Inference for a Random Coefficient Autoregressive Model. *Scandinavian Journal of Statistics* 5, 163-168.
- [223] Roll, R., 1984. A Simple Implicit Measure of The Effective Bid-Ask Spread in an Efficient Market. *Journal of Finance* 39(4), 1127-1139.
- [224] Ross, S.A., 1976. The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory*, 13(3), 341-360.
- [225] Scholes, M., Williams, J.T., 1977. Estimating Betas from Nonsynchronous Data. *Journal of Financial Economics* 5(3), 309-327.
- [226] Schwartz, E., Smith, J.E., 1997. Short-Term Variations and Long-Term Dynamics in Commodity Prices. UCLA Working Paper.

- [227] Sharpe, W.F., 1964. Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *Journal of Finance* 19(3), 425-442.
- [228] Sharpe, W.F., Alexander, G., 1990. Investments, 4th ed. Prentice-Hall.
- [229] Shiller, R.J., 1981. The Use of Volatility Measures in Assessing Market Efficiency. *Journal of Finance* 36, 291-304.
- [230] Shiller, R.J., 1984. Stock Prices and Social Dynamics. *Brookings Papers on Economic Activity* 2, 457-498.
- [231] Shleifer, A., Vishny, R.W., 1997. The Limits Of Arbitrage. *Journal of Finance* 52(1), 25-55.
- [232] Siegel, J., 1998. Stocks for the Long Run: The Definitive Guide to Financial Market Returns & Long-Term Investment Strategies. McGraw-Hill Companies.
- [233] Sullivan, R., Timmermann, A., White, H., 1999. Data-Snooping, Technical Trading Rules and the Bootstrap. *Journal of Finance* 54, 1647-1692.
- [234] Summers, L.H., 1986. Does the Stock Market Rationally Reflect Fundamental Values? *Journal of Finance* 41, 591-60.
- [235] Sweeney, R.J., 1988. Some New Filter Rule Tests: Methods and Results. *Journal of Financial and Quantitative Analysis* 23, 285-300.
- [236] Taylor, N., Van Dijk, D., Franses, P.H., Lucas, A., 2000. SETS, Arbitrage Activity, and Stock Price Dynamics. *Journal of Banking and Finance* 24(8), 1289-1306.
- [237] Taylor, S.J., 1986. Modelling Financial Time Series. Wiley, Chichester.
- [238] Urrutia, J.L., 1995. Tests of Random Walk and Market Efficiency for Latin American Emerging Equity Markets. *Journal of Financial Research* 18(3), 299-309.

- [239] Valkanov, R., 2003. Long Horizon Regressions: Theoretical Results and Applications. *Journal of Financial Economics* 68, 201-232.
- [240] Van Der Hart, J.V., Slagter, E., van Dijk, D., 2003. Stock Selection Strategies in Emerging Markets. *Journal of Empirical Finance* 10, 107-134.
- [241] Van Horne, J.C., Parker, G.C.C., 1967. The Random Walk Theory: An Empirical Test. *Financial Analysts Journal* 23, 87-92.
- [242] Watts, R., 1973. The Information Content Of Dividends. *Journal of Business* 46(2), 191-211.
- [243] White, H., 2000. A Heteroskedastic-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica* 48, 817-838.
- [244] White, H., 2000. A Reality Check For Data Snooping. *Econometrica* 68(5), 1097-1126.
- [245] Wright, J.,H., 1999. Long Memory in Emerging Markets Stock Returns. *Board of Governors of the Federal Reserve System International Finance Discussion Papers* 650.
- [246] Wright, J.,H., 2001. Long Memory in Emerging Market Stock Returns. *Emerging Markets Quarterly* 50(1), 50-55.

Appendix 2.1

Substituting expression (2.21) into (2.22) in the main text of Chapter 2 we obtain the one-period autocorrelation coefficient.

$$\begin{aligned}\hat{\lambda}_{\Delta} &= \frac{\text{Cov}[q(t+\Delta) - q(t) + (z(t+\Delta) - z(t)), (q(t) - q(t-\Delta)) + (z(t) - z(t-\Delta))]}{\text{Var}[(q(t) - q(t-\Delta)) + (z(t) - z(t-\Delta))]} \\ &= \frac{\text{Cov}[q(t+\Delta) - q(t), q(t) - q(t-\Delta)] + \text{Cov}[z(t+\Delta) - z(t), z(t) - z(t-\Delta)]}{\text{Var}(q(t) - q(t-\Delta)) + \text{Var}(z(t) - z(t-\Delta))},\end{aligned}\tag{A1}$$

where the last equality follows from the assumption that the q and z processes are uncorrelated.

We first evaluate the covariance and *variance* terms of the temporary component in expression (A1). Expression (2.11), using the definitions in (2.13) and (2.15), implies that:

$$z(t+\Delta) - z(t) = \theta + z(t)(e^{-\beta\Delta} - 1) + \epsilon_{t+\Delta}.$$

Therefore, the second covariance term in the numerator of expression (A1) becomes after substitutions:

$$\begin{aligned}&\text{Cov}(z(t+\Delta) - z(t), z(t) - z(t-\Delta)) = \\ &= \text{Cov}(\theta + z(t)(e^{-\beta\Delta} - 1) + \epsilon_{t+\Delta}, z(t) - z(t-\Delta)) \\ &= (e^{-\beta\Delta} - 1) \text{Var}(z(t)) - (e^{-\beta\Delta} - 1) \text{Cov}(z(t), z(t-\Delta)).\end{aligned}\tag{A2}$$

We evaluate next the $\text{Cov}(z(t), z(t-\Delta))$ term in the last equality of expression (A2):

First, due to the (weak) stationarity of the $z(t)$ process, it follows that $\text{Cov}(z(t), z(t-\Delta)) = \text{Cov}(z(t), z(t+\Delta))$, which in turn is equal to: $\text{Cov}(z(t), z(t+\Delta)) = E(z(t)z(t+\Delta)) -$

$E(z(t))E(z(t+\Delta))$. Second, substituting in the last equation the solution for $z(t+\Delta)$ in eq.(2.11) after multiplying it by $z(t)$, using the definition for $\epsilon_{t+\Delta}$ in eq. (2.15), and observing that the unconditional mean $E(z(t)) = E(z(t+\Delta)) = \gamma$ from eq.(2.19), we obtain:

$$\begin{aligned}
Cov(z(t), z(t+\Delta)) &= \\
&= E[\gamma(1 - e^{-\beta\Delta})z(t) + e^{-\beta\Delta}(z(t))^2 + z(t)\epsilon_{t+\Delta}] - \gamma^2 \\
&= \gamma^2(1 - e^{-\beta\Delta}) + e^{-\beta\Delta}\left(\frac{\rho^2}{2\beta} + \gamma^2\right) - \gamma^2 \\
&= e^{-\beta\Delta}\frac{\rho^2}{2\beta},
\end{aligned} \tag{A3}$$

where in the second equality above we used the simple result: $E(z(t)^2) = Var(z(t)) + [E(z(t))]^2$, and we substituted for the unconditional variance of $z(t)$ given by expression (2.20). We also used the fact that $E(\epsilon_{t+\Delta}) = 0$.

Substituting expressions (2.20) and (A3) for $Var(z(t))$ and $Cov(z(t), z(t-\Delta))$ respectively, in the last equality of eq. (A2) we obtain:

$$\begin{aligned}
Cov(z(t+\Delta) - z(t), z(t) - z(t-\Delta)) &= \\
&= (e^{-\beta\Delta} - 1)\frac{\rho^2}{2\beta} - (e^{-\beta\Delta} - 1)e^{-\beta\Delta}\frac{\rho^2}{2\beta} \\
&= -(e^{-\beta\Delta} - 1)^2\frac{\rho^2}{2\beta},
\end{aligned} \tag{A4}$$

which is the second covariance term of the numerator in expression (A1).

The second variance term in the denominator of expression (A1) is evaluated as follows:

First, due to the stationarity of the $z(t)$ process, it follows that: $Var(z(t) - z(t-\Delta)) = Var(z(t+\Delta) - z(t))$, which after substitution from expression (2.11) and using the de-

definition of $\epsilon_{t+\Delta}$ in (2.15) becomes

$$Var(z(t+\Delta) - z(t)) = (e^{-\beta\Delta} - 1)^2 Var(z(t)) + Var(\epsilon_{t+\Delta}).$$

Second, substituting in the equation above the expressions for $Var(z(t))$ and $Var(\epsilon_{t+\Delta})$ given by eq. (2.20) and (2.16) respectively, we obtain:

$$\begin{aligned} Var(z(t+\Delta) - z(t)) &= (e^{-\beta\Delta} - 1)^2 \frac{\rho^2}{2\beta} + \frac{\rho^2}{2\beta} (1 - e^{-2\beta\Delta}) \\ &= -\frac{\rho^2}{\beta} (e^{-\beta\Delta} - 1). \end{aligned} \quad (A5)$$

Now we concentrate on the evaluation of the terms

$Cov(q(t+\Delta) - q(t), q(t) - q(t-\Delta))$ and $Var(q(t) - q(t-\Delta))$ which are related to the random walk (permanent) component of the returns process. Using expression (2.10) we obtain:

$$q(t+\Delta) - q(t) = \alpha\Delta + \sigma \int_t^{t+\Delta} dW_1(\tau) \quad (A6)$$

and

$$q(t) - q(t-\Delta) = \alpha\Delta + \sigma \int_{t-\Delta}^t dW_1(\tau). \quad (A7)$$

Substituting expressions (A6) and (A7) in $Cov(q(t+\Delta) - q(t), q(t) - q(t-\Delta))$ it follows that:

$$\begin{aligned} &Cov(q(t+\Delta) - q(t), q(t) - q(t-\Delta)) \\ &= Cov\left(\alpha\Delta + \sigma \int_t^{t+\Delta} dW_1(\tau), \alpha\Delta + \sigma \int_{t-\Delta}^t dW_1(\tau)\right) \\ &= Cov\left(\sigma \int_t^{t+\Delta} dW_1(\tau), \sigma \int_{t-\Delta}^t dW_1(\tau)\right) = 0, \end{aligned} \quad (A8)$$

since non-overlapping increments of standard Brownian motion are independent.

Next, using expression (A7) we have

$$Var(q(t) - q(t - \Delta)) = Var\left(\alpha\Delta + \sigma \int_{t-\Delta}^t dW_1(\tau)\right) = \sigma^2\Delta \quad (\text{A9})$$

Substituting expressions (A4), (A5), (A8), and (A9) in eq. (A1), we obtain after simple rearrangements:

$$\hat{\lambda}_{\Delta} = \frac{-\left(e^{-\beta\Delta} - 1\right)^2 \frac{\rho^2}{2\beta}}{-\frac{\rho^2}{\beta}(e^{-\beta\Delta} - 1) + \sigma^2\Delta}$$

■

Appendix 2.2

We show below how the standard error of the all-important mean-reverting parameter β is obtained. If the number of observed returns goes to infinity, the number of observations is denoted by T , and the estimator of β is denoted by $\hat{\beta}$, then the distribution of $\sqrt{T}(\hat{\beta} - \beta)$ tends to the normal distribution with mean zero and variance which is a function of β . Parameter β is identified from:

$$\beta = -\ln \left\{ \left[\frac{Cov(r(t, t + 2\Delta), r(t - 2\Delta, t))}{Cov(r(t, t + \Delta), r(t - \Delta, t))} \right]^{\frac{1}{2}} - 1 \right\} \quad (B1)$$

Each covariance term in the above expression can be obtained as the product of the regression coefficient in the corresponding autoregressive equation and the variance of the dependent variable:

$$Cov(r(t, t + \Delta), r(t - \Delta, t)) = \lambda_{\Delta} * var(r(t, t + \Delta)) \quad (B2)$$

$$Cov(r(t, t + 2\Delta), r(t - 2\Delta, t)) = \lambda_{2\Delta} * var(r(t, t + 2\Delta)) \quad (B3)$$

Therefore, β can be expressed as

$$\beta = -\ln \left\{ \left[\frac{\lambda_{2\Delta} * var(r(t, t + 2\Delta))}{\lambda_{\Delta} * var(r(t, t + \Delta))} \right]^{\frac{1}{2}} - 1 \right\} \quad (B4)$$

The null hypothesis to be tested is that $\beta = 0$. The estimated variance of $\hat{\beta}$ is obtained under the null by

$$var(\hat{\beta}) = \left(\frac{\partial \hat{\beta}}{\partial \lambda_{\Delta}} \right)^2 \widehat{var}(\lambda_{\Delta}) + \left(\frac{\partial \hat{\beta}}{\partial \lambda_{2\Delta}} \right)^2 \widehat{var}(\lambda_{2\Delta}) + 2 \left(\frac{\partial \hat{\beta}}{\partial \lambda_{\Delta}} \right) \left(\frac{\partial \hat{\beta}}{\partial \lambda_{2\Delta}} \right) \widehat{cov}(\lambda_{\Delta}, \lambda_{2\Delta}) \quad (B5)$$

The standard error of $\hat{\beta}$ is therefore approximated by the square root of $\frac{var(\hat{\beta})}{T}$. The standard errors of the volatility parameters σ and ρ are obtained in a similar fashion.